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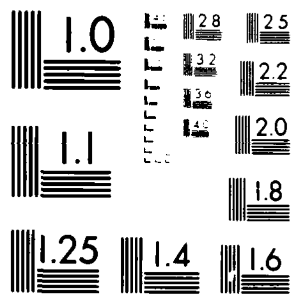

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AN ANALYSIS OF FORECASTING
TECHNIQUES FOR WHOLESALE DEMAND:
THE APPLICABILITY OF
MULTI-MODEL FORECASTING

Grace Ann Bittel, First Lieutenant, USAF
Daniel L. Gartner, GS-12

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This study focuses on determining if a multi-model forecasting strategy produces a more accurate demand forecast than the present eight-quarter simple moving average used in the Air Force Logistics Command D062 inventory control system. The analysis uses ten years of actual expendable (non-recoverable) data. This research analyzes the following forecasting techniques: naive, simple moving average (4, 8, and 12 periods), double moving average (4, 8, and 12 periods), single exponential smoothing (alpha of 0.2 and 0.8), single exponential smoothing with trend, focus forecasting, simple regression, S-curve analysis, exponential growth and eclectic methods. The analysis compares the fifteen techniques in terms of the mean absolute deviation (MAD) and percentage change, tracking signal, and variance. Also the statistical test, Oneway Analysis of Variance (ANOVA) compares the forecasting technique results. The results show simple exponential smoothing with an alpha of 0.2 as the forecasting model with the lowest MAD and variance. The techniques of simple moving average (4 and 8 periods) and simple exponential smoothing (alpha=0.8) exhibit very similar results. The ANOVA test shows no significant difference between the eclectic method and the top twelve techniques. However, from the other test results, the eclectic method and focus forecasting performed somewhat inferior for the data tested.

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AN ANALYSIS OF FORECASTING TECHNIQUES FOR WHOLESALE DEMAND: THE APPLICABILITY OF MULTI-MODEL FORECASTING

A Thesis

Presented to the Faculty of the School of Systems and Logistics

of the Air Force Institute of Technology

Air University

In Partial Fulfillment of the Requirements for the

Degree of Master of Science in Logistics Management

By

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First Lieutenant, USAF

Daniel Lee Gartner, BA
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September 1982

Approved for public release;
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This thesis, written by

First Lieutenant Grace Ann Bittel

and

Mr. Daniel Lee Gartner

has been accepted by the undersigned on behalf of the faculty of the School of Systems and Logistics in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE IN LOGISTICS MANAGEMENT

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John R Folkeson Jr

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CHAPTER I

INTRODUCTION

Background

In recent years, increased emphasis has been placed on improving decision making both in business and government. This emphasis is especially noteworthy in the area of predicting organizational customer demand requirements. Demand is defined as the quantity of goods buyers are willing to purchase at a specific price and time frame (Makridakis, 1973:201). Resource managers in every organization include demand requirements in their decision-making process. Thus, the accurate and timely prediction of demand requirements provides an essential input for managerial decision making.

One technique for predicting demand requirements is forecasting. Forecasting "predicts future values of a variable based on known or past values of that variable or other related variables [Wheelwright, 1977:684]." As the literature review in Chapter II points out, forecasting can be used to predict a wide variety of variables. Each organization determines the specific variables used in a given forecast.

The key aspect of any decision-making situation is finding the correct mixture of variables for predicting the circumstances surrounding the decision and the situation. With the right combination, forecasting improves demand requirement predictions. Therefore, forecasting must correlate directly with the resource management decision-making process.

Forecasting in any decision-making environment involves three key elements. The first element, time, correlates directly with the computation of future demand situations. Forecasts are made for specific points in time. The changing of that particular time period generally affects the outcome of the forecast. The second element, uncertainty, is present in all forecasting situations. If managers were certain about their predictions, it would be trivial to prepare a forecast. Managers make decisions based on the information obtained in the forecast. The third element is the reliability of a forecast. The amount and accuracy of information contained in the historical data directly impacts the reliability of the data and the forecast (Makridakis, 1973:3).

Managers, by considering the elements of time, uncertainty, and reliability, can use forecasting for customer demand predictions. Forecasting alleviates some of the uncertainty associated with future demand. This uncertainty causes management problems in meeting actual customer demand requirements. Managers may deal with this uncertainty by always having enough inventory on hand or by improving the predictions associated with inventory.

Managers use inventories as idle usable resources. These resources include raw materials, work in process, finished goods, people, and equipment. Inventories safeguard against the variability in delivery and demand. Inventory control is the set of policies used by managers for monitoring the levels of inventory, the required maintenance, and the replenishment cycle of the demand items. Proper inventory levels reduce the possibilities of stockouts, production stoppages, and backorders. Also high levels of inventory involve high carrying costs and the risks of obsolescence (Chase and Aquilano, 1981:461). Therefore, it is sometimes difficult for the manager to have enough inventory on hand for demand requirements.

This research centers around improving predictions associated with demand requirements through the use of forecasting techniques. The problem arises in determining a forecasting technique which most accurately forecasts an organization's needed requirements.

This research investigated the general problem of finding a forecasting strategy pertaining to the Air Force's inventory demand requirements. Specifically, the research involves inventory demand requirements for expendable items. Expendable items are items consumed and not reparable. These items are discarded after use. The current management system for expendable items is the Air Force Logistics Command D062 system. The D062 system uses a forecasting strategy for prediction of expendable item demand requirements.

The Air Force Logistics Command (AFLC) is responsible for supplying weapon system parts and accessories. This command consists of five Air Logistics Centers (ALCs). These ALCs are responsible for supporting Air Force bases worldwide and a growing list of foreign military customers. The management of such a complex support system requires the most accurate forecasting techniques available. Finding the most accurate technique is a basic problem in formulating a forecasting strategy.

The major problem addressed by this research is the identification and evaluation of different forecasting techniques using actual AFLC historical demand data. If it can be shown a better technique exists, significant cost savings could be achieved.

Research Problem Statement

One of the basic problems in a forecasting strategy is to establish the appropriate model which most accurately forecasts the actual demand. The current AFLC D062 inventory control system uses the eight-quarter simple moving average as its forecasting technique. This research will address the problem of determining if a more accurate forecasting technique can be identified for the D062 inventory control system.

Research Objectives

The primary objectives of this research effort are to:

1. Study the appropriateness of various forecasting strategies for a sample of expendable items in the AFLC inventory system.

2. Develop and test several forecasting models which are applicable to segments of this inventory system.

3. Determine if a more accurate forecasting strategy can be recommended for the present system.

Research Hypothesis

This thesis will test the following hypothesis in connection with the stated objectives: *A multi-model forecasting strategy produces a more accurate demand forecast than the present eight-quarter simple moving average used in the D062 inventory control system.*

Organization

This thesis is organized into five chapters and an appendix. Within this first chapter the reader was introduced to background material, the problem statement, research objectives, and the research hypothesis identified with this research effort. In Chapter II the purpose and introduction is followed by a comprehensive investigation of the various available forecasting techniques. Chapter III contains the methodological details of the research. It also outlines the proposed models and the evaluation criteria. Chapter IV presents the data analysis and results. Chapter V completes the research by describing the researchers' conclusions and recommendations.

CHAPTER II

LITERATURE REVIEW

Purpose

This chapter reviews the different forecasting techniques applicable to inventory control systems. This involves both qualitative and quantitative forecasting techniques. Each technique is reviewed in detail to determine its significance.

This literature review compares a number of forecasting techniques available to the Air Force Logistics Command (AFLC) inventory system. The current AFLC inventory control system might improve if a better forecasting technique is used. The current Air Force inventory system is set up to use qualitative and quantitative forecasting techniques. Therefore, both qualitative and quantitative techniques will be discussed.

In selecting a "best" forecasting technique, six basic criteria need to be considered. These consist of time horizon, data pattern, model type, cost, accuracy, and applicability. Time horizon deals with the span of time into the future that best suits the forecasting problem. The data pattern is important because the appropriate technique needs to be matched with the presumed pattern. The model type of the forecasting technique should correspond to the model of the situation being forecasted. Cost has an obvious impact on which method to employ. Accuracy is closely related to the level of detail required in the forecast. The ease of application is a definite attraction for certain forecasting methods. All of the above criteria were considered in establishing the proposed forecasting models for this research.

All forecasting methods identify and use some existing data pattern or relationship as the basis for preparing a forecast. Each quantitative technique makes explicit assumptions about the type of underlying data pattern. The six types of time series data demand patterns are average (horizontal), trend, seasonal, cyclical, autocorrelation, and random. An average pattern exists when the data are evenly distributed over a certain time period. A trend pattern occurs when the data increases or decreases over a certain time period. In a seasonal pattern, the data is influenced by seasonal factors such as the months of the year. A cyclical pattern exists when the data are influenced by long-term factors such as economic fluctuations. The major distinction between a seasonal and a cyclical pattern is the seasonal pattern recurs on a regular basis. Autocorrelation occurs when the value expected at any point in time is highly correlated with its own past values. A random pattern is caused by natural chance variation (Chase, 1981:68-69).

Quantitative forecasting techniques consist of time series, causal and multi-model methods. The qualitative methods include the Delphi method, market research, and technological forecasting.

The time series analysis methods of moving average, exponential smoothing, Box-Jenkins, and decomposition analysis predict future occurrences based on a set of past data (Chase, 1981:69). Time series is most appropriate for short-term forecasting with a relatively stable variable such as sales of an old established product (Sullivan, 1977:21).

The causal methods of regression and econometric modeling assume the forecasted (dependent) variable exhibits a cause-effect relationship with one or more independent variables (Joyeux, 1980:8). Causal methods are suitable techniques for longer-term forecasting such as ascertaining major turning points and giving forecast impacts on major policy decisions (Sullivan, 1977:23).

Multi-model methods consist of focus, combination, and eclectic forecasting. [Eclectic forecasting is a term describing a multi-model technique developed in this research.] Multi-model methods incorporate computer simulation to determine the "best" forecasting approach.

Multi-model techniques can be used for almost any forecasting need such as inventory control, sales, and manpower requirements.

Qualitative methods of Delphi, market research, and technological forecasting are used when there is little or no relevant quantitative data. They rely largely on human judgement. These methods may be used to forecast long-term corporate planning, consumer tastes and fashion changes (Sullivan, 1977:204).

Quantitative Methods

Time Series Analysis

Smoothing Techniques. The basic premise behind smoothing techniques is some underlying pattern in the values of the variable being forecast. The actual values of the variable will incorporate both the underlying pattern and random fluctuations. The smoothing techniques average or smooth the values so that extreme values in a historical sequence are eliminated. Smoothing techniques are classified into two groups: a broad horizontal pattern in which the variable does not grow or decline significantly over time, and a pattern with a trend or fluctuation. Moving average and exponential smoothing are the appropriate techniques for a horizontal data pattern. Double exponential smoothing, linear growth models, and time series regression are the major techniques used when forecasting trend data with little variation existing about the trend (Firth, 1977: 38-40).

Moving Averages. In the simple moving average technique a time period containing a number of data points is averaged by dividing the sum of the point values by the number of points (Clarke, 1976:94). This is a way of reducing the impact of random fluctuations by taking an average of several period's values. The premise here is the random element in a period's results can be either positive or negative. By taking a number of period's results the positive and negative random elements will tend to cancel themselves out (Firth, 1977:42). The main assumption is the existence of several historical observations. Moving average responds only to a horizontal data pattern (Wheelwright, 1977:32). The moving average technique is described notationally as

$$F_{t+1} = \frac{V_t + V_{t-1} + V_{t-2} + \ldots V_{t-N+1}}{N} = \frac{1}{N} \sum_{i=t-N+1}^{t} V_i \qquad (2.1)$$

where,

F_{t+1} = forecast for the next period, t+1;

$V_{t;t-1;t-2}\ldots$ = the actual value of the variable at t, t-1, t-2...; and

N = the number of observations used in the average (Firth, 1977:43).

The smaller the number of observations, the greater is the response of the moving average to any changes in the data. If the data is highly influenced by random elements, then the forecast may be very poor. If the data is changing because of fundamental factors, then the moving average based on a small number of observations gives the best forecast.

The major limitations in the simple moving average technique are:

1. That equal weighting is implicitly given to the various observations included in the moving average.

2. That it disregards data prior to the period t-N+1.

3. If the variable being forecast does not follow a broadly horizontal pattern or if it jumps to a new horizontal pattern, then the technique is not really suitable.

4. The large amount of data that needs to be available and stored.

5. The historical data used may affect the forecast (Firth, 1977:46-47).

The double moving average technique is similar to the simple moving average technique. A forecast is prepared by taking the difference between the single moving average and the double moving average and adding this difference to the single moving average. The basis of this method is to calculate a second moving average. This double moving average is a moving average of the moving averages based on the actual data. Makridakas (Wheelwright, 1977:41-44) states the double moving average has the advantage of forecasting data with a trend pattern. However, this technique does not match the accuracy of double exponential smoothing. The large number of data points needed for calculation limits this technique.

Weighted Moving Average. The weighted moving average technique explicitly attaches weights to the data. Two possible weighting systems are the decimal method and the fractional method.

$$\text{(Decimal)}\ F_{t+1} = 0.4V_t + 0.3V_{t-1} + 0.2V_{t-2} + 0.1V_{t-3} \quad (2.2)$$

$$\text{(Fractional)}\ F_{t+1} = \frac{16V_t + 8V_{t-1} + 4V_{t-2} + 3/32V_{t-3} + 1/32V_{t-4}}{32} \quad (2.3)$$

where,

F_{t+1} = forecast for the next period, t+1; and

$V_{t,t-1,t-2}...$ = the actual value of the variable at time t,t-1,t-2...

The actual decimal or fractional weights can be adjusted to various values (Firth, 1977:47). Chase (1981:72) states, "Weighted moving average has a definite advantage over the simple moving average in being able to vary the effects of past data."

Exponential Smoothing. Exponential smoothing is similar to weighted moving average. However, this technique gives more weight to recent data points and is dependent on the value of alpha. Descriptively, the new forecast is equal to the old one plus some alpha (α) which is a proportion of the past forecasting error (Trigg, 1967:55). It involves weighting past data with weights that decrease exponentially with time. The weights attached to each observation are thus

$$\alpha V_t + \alpha(1-\alpha)V_{t-1} + \alpha(1-\alpha)^2 V_{t-2} + \alpha(1-\alpha)^3 V_{t-3} \ldots + \alpha(1-\alpha)^n V_{t-n} \quad (2.4)$$

where,

V = individual observations for each period t to t-n, and

α = a value which lies between zero and one.

The series is summed and this gives the exponential smoothed forecast for period t+1. The closer α is to 1, the greater the new forecast will incorporate an adjustment for the error in the immediately prior forecast; the nearer α is to 0 the less sensitive the new forecast will be to the error in the immediately prior forecast (Firth, 1977:47-48). In practice, equation (2.4) can be represented as

$$F_{t+1} = V_t + \alpha(V_t - F_t) \quad (2.5)$$

Gardner concludes:

> . . . exponential smoothing is simple and inexpensive, and there is no evidence that the more complex and expensive forecasting models, such as Box-Jenkins, consistently provide better short-range forecast accuracy.

Exponential smoothing is often considered a superior forecasting technique than moving averages because:

1. It gives greater weight to more recent data.
2. It incorporates all past data since the initiation of the technique; therefore, there is no artificial cutoff point.
3. It requires less data to be held in storage than the longer period moving average methods.
4. Adaptations of the model can easily be made to account for changing conditions. This is facilitated by altering the value of α. Altering other moving average methods is generally more costly (Firth, 1977:51).

The technique of double exponential smoothing prepares a forecast by taking the difference between the single exponential smoothing and the double exponential smoothing and adjusting for a trend data pattern. It has the advantage of handling horizontal and trend data patterns (Wheelwright, 1977:44,47). It can be expressed as

$$F''_{t+1} = \alpha F'_{t+1} + (1-\alpha) F''_t \qquad (2.6)$$

using equation 2.5 as the value for F'_{t+1}.

Various double exponential smoothing techniques are used to forecast trend data. The following techniques are most widely used in trend analysis.

1. Brown's One-Parameter Linear Exponential Smoothing. It is preferred for nonstationary, nonseasonal data. The trend is adjusted by taking the difference between the single and double smoothed values and adding to the single smoothed value (Trigg, 1967:61). An α of 0.1 gives a conservative forecast, while an α of 0.2 gives a more responsive forecast (Trigg, 1967:78).

2. Holt's Two-Parameter Linear Exponential Smoothing. It uses two smoothing constants, α and γ (values between 0 and 1) to smooth trend values directly. This provides greater flexibility because the trend is smoothed with a parameter different from the original forecast (Trigg, 1967:64).

3. Brown's Quadratic Exponential Smoothing. It is used when the basic underlying pattern is quadratic, cubic, or higher (Trigg, 1967:64). It has only one parameter whose value is usually close to 0.1. It can predict turning points better than linear smoothing because it is quadratic. A weakness is it overreacts to random changes but this disadvantage can be reduced by setting α below 0.1 (Trigg, 1967:79).

4. Adaptive-Response-Rate Single Exponential Smoothing (ARRSES). This method does not require

specification of a value for α. It can change the value of α on an ongoing basis in which the initial α value is no longer valid. It is especially useful when a large amount of items require forecasting (Trigg, 1967:53).

Makridakis states,

> Exponential smoothing has been applied extensively in a number of business situations because it is easy to understand, straightforward to apply, and intuitively appealing to the manager. Control exists over the weights through the assignment of a value for alpha (α). A major drawback is an easy way does not exist for determining an appropriate value of α [Wheelwright, 1977:50].

Classical Decomposition Technique. The decomposition technique separates the underlying pattern of a time series into cyclical, seasonal, and trend subpatterns. These subpatterns are individually analyzed, extrapolated, and recombined to obtain forecasts of the original series (Wheelwright, 1978:679). Classical decomposition provides an analysis of historical data in each subpattern (Wheelwright, 1977:95). The traditional form of the classical decomposition model is

$$V_i = T_i \times S_i \times C_i + I_i \qquad (2.7)$$

where,

V = value of the variable;

T = trend factor;

S = seasonal factor;

C = cyclical factor;

I = irregular factor, i.e., the random element in the time series; and

i = period i.

Decomposition analysis has the following advantages:

1. It allows the forecaster to determine the long-term trend of the variable.

2. It gives data on which the forecaster and management can make short-term plans.

3. It can be used to forecast a variety of business situations (Firth, 1977:63-65).

Makridakas (Wheelwright, 1978:91) points out the limitations associated with classical decomposition. It assumes a time-series pattern which means causal relationships cannot be represented. It is nonstatistical in nature and the costs can be substantial if computation of seasonal, trend, and cyclical factors are required.

The methodology involved in classical decomposition is:

1. Calculate the seasonal factor. This involves the ratio of the actual to the moving average method.

2. Calculate the trend factor. This is computed from a simple linear regression analysis of moving averages on time.

3. Calculate the cyclical factor. This is found by dividing the moving average by the trend factor.

4. The forecast is made by substituting in the values of the trend factor, the seasonal factor and the cyclical factor for the time period into the equation $F_t = T_t \times S_t \times C_t$ where t stands for period t (Firth, 1967:65).

Adaptive Methods. Adaptive forecasting is the description given to methods which adapt to a particular data pattern. The basis of the methods is that the weightings used in the particular technique adjust as new data accrues. Adaptive techniques are especially important when the variable is nonstationary since the forecasts respond quickly to changes in the data (Firth, 1967:82).

Two types of adaptive forecasting methods are:

1. Chow's Adaptive Control Method. It is similar to ARRSES but it has the advantage of being used for non-stationary data. The α is "adapted" by small increments, usually 0.05 (Wheelwright, 1977:75).

2. Brown's One-Parameter Adaptive Method. This method involves a single smoothing constant δ, which smooths the current value of the errors. It is more useful when combined with that of formulating the forecast based on previous values of the series (Wheelwright, 1977: 75).

Adaptive Filtering. Adaptive filtering is based on moving averages in which the specific data points have their own individual weights. The method requires the initial weightings to be estimated and adjusted by a learning constant. The adjustment is expressed as

$$W^* = W + 2KeV \tag{2.8}$$

where,

W^* = revised set of weights,

W = old set of weights,

K = learning constant,

e = error of the forecast, and

V = values of the variable (Firth, 1977:82).

The major techniques which use an adaptive filtering process are the Trigg and Leach's method, and the Box-Jenkins forecasting technique.

Trigg and Leach's Method. Trigg and Leach's method is simi ar to exponential smoothing but instead of using α, the value of Trigg's tracking signal is used. The value of the tracking signal (S_t) changes according to the volatility of the data. The Trigg and Leach forecasting method is

$$F_{t+1} = S_t V_t + (1-S_t)F_t \tag{2.9}$$

where,

F_{t+1} = forecast n periods ahead,

V_t = value of variable at time t,

F_t = forecast at time t, and

S_t = tracking signal value (positive value) (Firth, 1977:82).

Firth states,

> Trigg and Leach's method provides a model which is very responsive to sudden changes in data and represents a considerable improvement over exponential smoothing. The model can be adapted for linear and seasonal trend data [Firth, 1977:88].

Box-Jenkins Technique. Clarke (1976:59) describes Box-Jenkins as a highly sophisticated technique which identifies patterns in the historical values of a time series and extrapolates these patterns into a forecast. Woodworth (Hill, 1980:413) quotes Anderson,

> The relevantly recent research work of Box and Jenkins is now proving itself such an effective tool for letting the data speak for themselves that no provider of forecasts can afford to ignore it, and no policy maker should be ignorant of its power [Anderson, 1977:14].

The Box-Jenkins approach is described by the diagram in Figure 1-1.

The Box-Jenkins approach postulates three general classes of models which can describe any time series pattern. The first two models, autoregressive (AR), and moving average (MA) are combined to form the third model, autoregressive integrated moving average (ARIMA).

Box-Jenkins forecasting has the advantage of handling a wide range of time series patterns and providing accurate statistical information (Clarke, 1976:59).

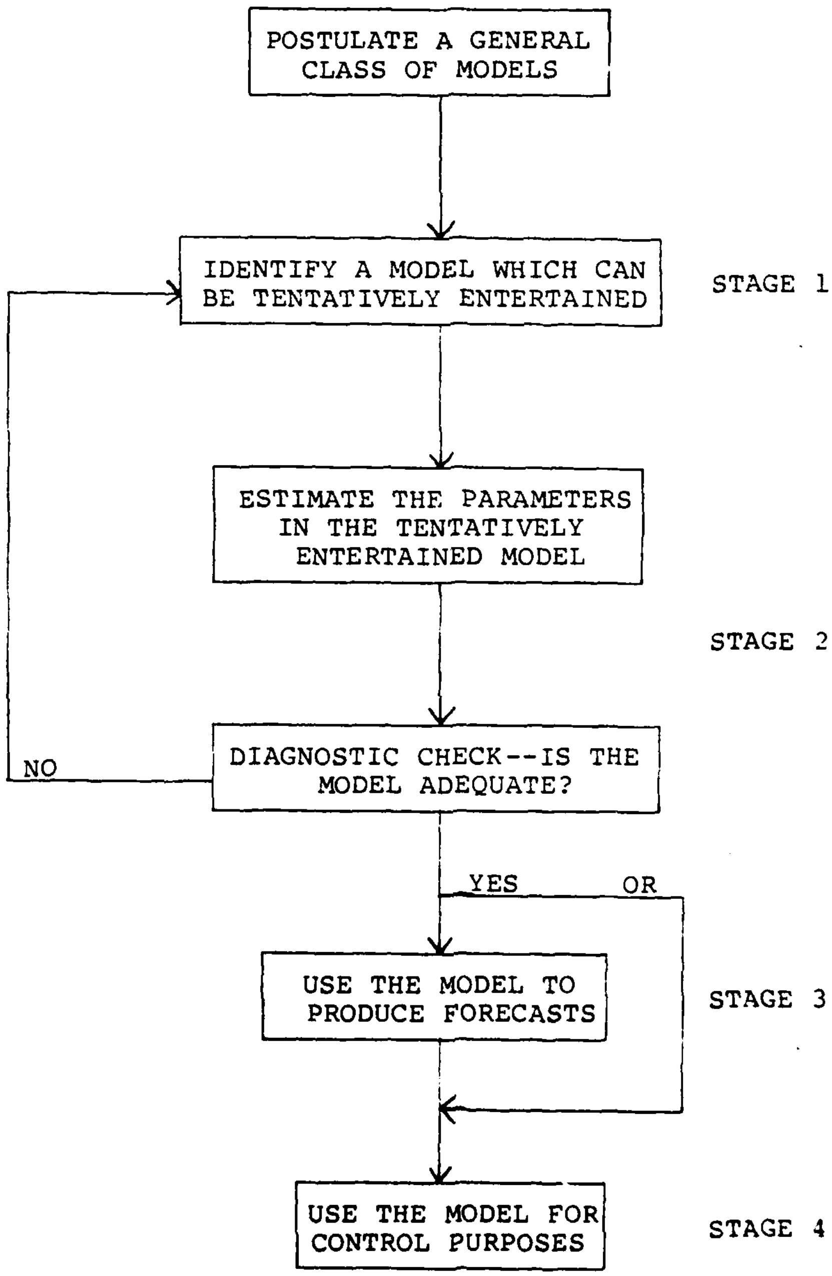

Fig. 1-1. Box-Jenkins Technique

The main disadvantages are cost and complexity in comparison with multiple regression and classical decomposition (Wheelwright, 1977:135). In the final analysis, it is up to the user to decide when the benefits of higher accuracy will compensate for the higher cost associated with Box-Jenkins.

Causal Methods

Regression Techniques. Regression analysis is a statistical technique which fits the specified model to the available historical data (Chambers, 1971:60). Clarke states:

> One of its major attractions is that, as independent variables take on new values, the dependent variable will also change. Thus it goes beyond simple time series extrapolations and bases a forecast on a causal relationship [Chambers, 1971:61].

Regression models are quantified descriptive causal models. The major advantages of causal models over time series methods are:

1. Causal models search for the underlying factors affecting the value of a variable.

2. The forecast produced from the causal model can be expressed as a range of outcomes and the reliability of the forecast can be expressed in objective probabilistic terms.

3. The impact of changing policies relating to controllable variables can be measured (Firth, 1977:100).

The main disadvantages associated with regression models are:

1. Regression models require a large amount of data.

2. Substantial cost associated with collecting the data.

3. The time involved in developing the initial regression equation.

4. The need to monitor the causal relationship between the independent variable and the dependent variable. If this relationship changes, a new set of data needs to be analyzed for determination of the most appropriate regression equation (Wheelwright, 1977:122).

Simple Linear Regression. Simple linear regression assumes a linear relationship exists between two variables. It is a causal model which involves only one independent variable. The simple linear regression model can be described by the equation

$$F_{t+1} = a = bX_t + U_t \qquad (2.10)$$

where F_{t+1} is the dependent variable and X is the independent variable. The terms a and b are regression coefficients, where a is a constant, and b represents the change in the value of F_{t+1} for a one-unit change in X. The value b represents the slope of the line. The term U represents the error term. The values of a and b can be determined by the least squares method. This method minimizes the sum of the squared deviations for all the observations. The deviations represent the differences between the actual observation and the corresponding value on the straight line (Firth, 1977:101-104).

Wheelwright (1978:66) shows simple regression analysis has the advantage of forecasting both causal and time-series models. Parker (1971:107) states the main contribution of regression analysis is the statistical precision with which it measures relationships and indicates their reliability. Parker (1971:109) concludes, "through regression it is feasible to analyze far greater quantities of data than is possible with an intuitive or manual method [Wheelwright, 1978:66]."

Wheelwright (1978:66) discusses the limitations of regression analysis. It is limited to linear relationships, requires a considerable amount of data to produce statistically significant results, and treats all data observations as equal.

Multiple Regression Analysis. Multiple regression analysis uses several independent variables to predict the value of some dependent variable. It has the same strengths and limitations as simple regression analysis. Chase (Clarke, 1976:86) points out the specific limitations of data gathering and mathematical computation. He further clarifies that standard computer programs are available for multiple regression analysis.

As with simple linear regression, the technique of least squares regression can be used with multiple regression analysis. In using regression analysis the requirements of linearity, multicollinearity, autocorrelation, homoscedasticity, and the distribution of error terms need to be met. Linear regression assumes the independent variables are linearly related with the dependent variable. Statistical tests should show that the data fit a linear pattern. Multicollinearity occurs when two or more of the independent variables are highly correlated. Multicollinearity could have a significant impact on the forecast. The requirements of homoscedasticity, heteroscedasticity, and autocorrelation are concerned with the properties of the residuals of error terms. Homoscedasticity is the term referring to the error terms having a constant variance. Heteroscedasticity implies that one or more important independent variables are not in the model. The presence of heteroscedasticity can be detected by the Durbin Watson statistical test. Autocorrelation often occurs when the data are time series related. Autocorrelation suggests a systematic pattern in the residuals which implies an important independent variable has been left out of the regression. The final requirement is the residuals should be normally distributed (Firth, 1977:119-122).

The general equation for multiple linear regression has the following form when there are p independent variables (Sullivan, 1977:72).

$$F_y = a + b_1X_1 + b_2X_2 + \ldots + b_kX_k + \ldots b_pX_p \quad (2.11)$$

Makridakis concludes:

> Because of the substantial costs in initial development of a multiple regression program, it is generally used only for longer term forecasting in which the value of an accurate forecast is substantial [Wheelwright, 1977:122].

Econometric Models. The econometric model technique is an extension of regression analysis. An econometric model is a system of interdependent regression equations that describe some sector of economic sales or profit activity (Chambers, 1971:36). The aim of the model is to measure the impact of one economic variable against another in order to forecast future developments. The difficulty is the involvement of hundreds of variables and their interrelatedness makes it difficult to develop appropriate equations. To simplify the problem of dealing with these interrelationships, the variables are classified as endogenous or exogenous. Endogenous variables are determined within the system and include such factors as income and employment. Exogenous variables are determined by forces external to the system such as the physical limitations of nature (Sullivan, 1977:226-227).

Clarke (1976:59) describes econometric modeling as a system of simultaneous regression equations which allow mutual dependence among all variables. Chambers (1971:54) states "These models are relatively expensive to develop and can easily cost between $5000 and $10,000, depending on the detail." Wheelwright (1978:241) agrees econometric models are expensive to build and operate.

Input-Output Analysis. Input-output analysis consists of tables which show the transactions between component forms of a system. "The main use of input-output analysis is in the planning process and it has achieved a high rate of adoption at the national and regional levels [Firth, 1977: 160]." The major assumptions are: cost relationships are the same for all levels of production and the relationships hold true over time (Firth, 1977:163). Input-output tables are more useful as tracking devices for signalling when basic market changes have occurred. The major drawbacks to input-output tables stem from the large amount of data required for forecasting. Also, input-output tables are expensive long-range forecasting tools (Firth, 1977: 227-228).

Sullivan (1977:228) points out, "In a constantly changing technological economy, models must be updated continuously if they are to be meaningful." Chambers (1971:45) acknowledges "Corporations using input-output models have expended as much as $100,000 and more annually to develop useful applications."

Leading Indicators. Leading indicators relating to industrial and economic statistics indicate the value of direction of another variable. The purpose of leading indicators is to forecast the turning points of business cycles. Some of the most significant leading indicators in the literature are fiscal policy, monetary policy, GNP deflator, productivity, consumer spending, and the stock market (Sullivan, 1977:232-238). Leading indicators are used when the relationship will not fit regression methods (Firth, 1977:170-177). Chambers (1971:45) concludes, "Long-term accuracy with leading indicators is very poor."

Multi-Model Methods

Combination Forecasts. It is doubtful whether any forecasting technique can be thought of as optimal given all the information in the universe. Granger and Newbold state one way to improve on a given technique is to "consider two or more forecasts of the same quantity since it is often the case in macroeconomics that competing forecasts are available [Granger and Newbold, 1979:269]." It may be better to incorporate them all into an overall combined forecast.

Rather than to expound on the complex mathematical extrapolation of a combined forecast, an example presented in Granger and Newbold might be more apropos.

> One-step ahead forecasts of World airline passenger miles per month over the period 1951-1960 are given for both a Box-Jenkins model and an exponential smoothing model. The former yielded an error variance of 148.6 and the latter 177.7. However, an alternative forecast, which is simply the average of the two individual forecasts, can be shown to have an error variance of 130.2. Thus, in this particular instance, a combined forecast that outperforms both individual forecasts can readily be found [Granger and Newbold, 1979:269].

More sophisticated combination rules might lead to further improvement than presented in this example.

Focus Forecasting. Focus forecasting is a multi-model technique that employs simplistic forecasting assumptions and computer simulation to forecast demand. Bernard Smith, the originator of focus forecasting, established a "recipe approach" of different strategies to define all demand in terms of trends, cycles, seasons, and noise (Smith, 1978:5). Chase and Aquilano list the recipe approach as follows:

A. Whatever we sold in the last three months is what we will probably sell in the next three months.
B. What we sold in the same three-month period last year, we will probably sell in that three-month period this year. (This would account for seasonal effects.)
C. We will probably sell 10 percent more in the next three months than we sold in the last three months.
D. We will probably sell 50 percent more over the next three months than we did for the last three months last year.

E. Whatever percentage change we had last year in the past three months will probably be the same percentage change we will have over last year's in the next three months [Chase, 1981:89].

Smith states, "Focus forecasting uses simple strategies [Smith, 1978:33]." These simple strategies are fed into a computer along with historical data. The computer goes back in time three periods and pretends they didn't happen. The computer then "simulates" or, in this case, forecasts these three periods using each of the simple strategies. The computer then compares this simulated output with the actual data. "Whichever simple strategy best projects the three periods that have already happened is the one the computer uses to project the future [Smith, 1978:3]."

As Chase and Aquilano point out, "focus forecasting has significant merit when demand is generated outside the system [Chase, 1981:92]." Two important points need to be made regarding focus forecasting: (1) keep the strategies simple, and (2) ensure the people who will be using the forecasts are involved in creating the strategies (Chase, 1981:13).

Eclectic Forecasting. Eclectic forecasting is defined by this thesis as a technique incorporating two or more forecasting models in conjunction with computer simulation to forecast actual demand. Many computerized programs exist to analyze historical data and recommend several relevant forecasting techniques. These computerized programs can also provide statistical analysis of this data. When this information has been gathered, the recommended forecasting techniques would be similar to the recipe list used in focus forecasting. The difference being they may include highly sophisticated techniques and indeed may even include multi-model forecasting. The process used in focus forecasting with its simplistic computer simulation technique could then be employed to heuristically determine the method to be used to forecast future demand. In addition to using the above mentioned process which requires storing and updating actual demand data on the computer, sophisticated computer simulation could be used. If during statistical analysis, the historical demand data displays a particular distribution, then stochastic variables can be generated reducing the need to store the historical data.

Qualitative Methods

Delphi Method

The Delphi method is a qualitative method used in long-term and technological forecasting. It basically consists of a group of experts giving their own opinions and views as to the outcomes of specified variables. A consensus of the forecasts is obtained and used to forecast into the future (Firth, 1977:218). The Delphi approach's main difference from other qualitative methods is the use of a large number of independent experts to make forecasts. Some of the advantages of the Delphi method is its relatively low cost, versatility in application and minimal time requirements for the participants. Some of the most promising uses are:

1. It provides a structured means of studying the forecasting process.

2. It serves as a teaching tool that leads people into thinking in more directions and dimensions about the future.

3. It is an aid to probing into the goals and priorities of members of an organization.

The Delphi method has some distinct disadvantages. The main problems with this method are:

1. When using large numbers of experts and especially those from outside, problems may arise in accurately explaining the problem situation and what the expert is required to do.

2. It is sometimes difficult to rank qualitative answers from respondents.

3. Problems may arise relating to small group bias.

4. It can be quite expensive if many leading authorities are employed (Firth, 1977:220).

Market Research

Market research is "the systematic, formal, and conscious procedures for evolving and testing hypotheses about the real markets [Chambers, 1971:36]." Market research involves determining what the customer wants. The customer's goal is not to keep the forecaster in business. Most of the time the customer doesn't always know what he or she wants. If the customer does know, he may be unwilling to tell the forecaster what it is. Another consideration is what the customer says is wanted and what is actually wanted may be two different things. Finally, what the customer wants may not be what the customer needs (Wheelwright, 1978:664). Typical applications of this type of forecasting are forecasts of long-range and new product sales, and forecasts of margins (Chambers, 1971:36).

Technological Forecasting

Technological forecasting is a name given to a myriad of specialized forecasting techniques. Many of these techniques are extensions of methods already mentioned in this paper (Sullivan, 1977:191). Sullivan states,

> Technological forecasting provides procedures for data collection and analysis to predict future technological developments and the impacts such developments will have on the environment and lifestyles of mankind [Sullivan, 1977:191].

Technological forecasting is used to estimate the growth and direction of a technology. An important ingredient for good technological forecasting is a thorough understanding of technical history, current developments, and future trends relating to the technical issue (Sullivan, 1977: 192-193).

Technological forecasting techniques can be divided into the two broad categories of exploratory and normative forecasting. Exploratory forecasts are based on existent technology and provide predictions concerning future developments. Normative forecasts assume the existence of future technological innovation and provide methods for achievement. An important application of technological forecasting concerns the identification of goals, which is achieved by exploratory techniques. Based on these goals, normative techniques are used to determine a means of achieving these goals. Mainly this forecasting technique is used in specialized industrial situations by companies with large amounts of resources and data-gathering capabilities. Various government agencies are also large users of technological forecasting techniques (Sullivan, 1977:193-194).

Trend extrapolation is often used to make technological forecasts. This technique is based on a historic time-series for a selected technological parameter. A good trend extrapolation depends on selection and prediction of key performance parameters. An advantage of trend extrapolation is historical data are readily available.

A straight-line or fitted-curve projection of the future is easily understood and used. A drawback to extrapolation is it cannot predict unforeseen technology interactions. A technique known as historical analogy is a form of trend extrapolation that uses simple regression to project values of the performance parameter. Other trend extrapolation methods include substitution curve and envelope curve extrapolation. These methods rely on advanced trend analysis to fit the historical data and to project future trends. The substitution curve is based on the belief a product or technology which exhibits a relative increase in performance over the older product will substitute the one having the lesser performance. The relative increase in performance is the important factor in the substitution of one technology for another. Envelope curves, however, are based on the inventory process. A succession of different technologies emerges over a period of time to satisfy the demand for improvement of a given capability. Because any one technique seems to evolve along an S-shaped curve of capability improvement over time, a succession of these S-shaped curves is plotted against time. Envelope curves, like substitution curves, utilize time-series data to make forecasts. Substitut on curves forecast the amount of substitution of one technology for another at some future time. Envelope curves forecast future performance on the basis of past experience with several different technologies. Envelope curve forecasting would be useful in those industries experiencing rapid innovation (Sullivan, 1977:194-198).

Technological forecasting methods do not require data in the same manner as quantitative forecasting methods. The inputs required depend on the specific method. As with their quantitative counterparts, technological techniques vary widely in cost, complexity, and value. They can be used separately but are more often used in combination with each other or in conjunction with quantitative methods. It is difficult to measure the accuracy of technological forecasts. They are used mainly to provide hints, to aid the planner, and to supplement quantitative forecasts. They are used for medium and long-range forecasts because of their nature and cost.

Conclusion

The quantitative forecasting techniques of time series, causal, and multi-model methods were discussed with respect to their strengths and limitations. Quantitative forecasting methods have gained wide acceptance mainly because of their accurate performance and computer adaptation.

The qualitative techniques of Delphi, market research and technological forecasting were discussed according to their advantages and disadvantages.

Qualitative forecasting methods are generally applied only to important long-term decisions. This is mainly because of their preparation cost and difficulty.

The Air Force inventory system is set up to use both quantitative and qualitative forecasting procedures. Quantitative methods encompass a wide range of procedures. Table 1-1 outlines the forecasting techniques applicable to the D062 system.

In selecting the "best" forecasting technique the researchers considered the six basic criteria outlined in the introduction of this chapter. The criteria of time horizon, data pattern, model type, cost, accuracy, and applicability were instrumental in the selection of appropriate techniques for analysis. The techniques outlined in Table 1-1 were evaluated using the above criteria.

This literature review provides the basis for determining the forecasting strategies employed in this thesis methodology. The next chapter will discuss the specific methodology based upon the analysis of the historical demand data.

TABLE 3-1

FORECASTING TECHNIQUES TO BE UTILIZED

Criteria	Naive	Moving Average	Weighted Moving Average	Exponential Smoothing	Classical Decomposition	Adaptive Filtering	Trigg and Leach's Method	Box-Jenkins Technique	Simple Regression	Multiple Regression	Econometric Models	Input-Output Analysis	Leading Indicators	Focus Forecasting	Combination Forecasting	Eclectic Forecasting
Time Horizon																
Immediate Less Than One Month	X	X	X	X	X	X	X	X								X
Short One to Three Months	X	X	X	X	X	X	X	X		X	X		X	X	X	X
Medium Less Than Two Years	X					X	X	X	X	X	X				X	X
Long Two Years and More	X								X	X	X	X				X
Pattern of Data (Horizontal)																
Average	X	X	X	X	X	X	X	X				X	X			X
Trend	X				X	X	X	X	X	X	X			X	X	X
Seasonal	X				X	X	X	X						X	X	X
Cyclical	X				X	X		X						X		X
Autocorrelation	X				X			X				X				X
Random	X			X	X	X	X	X	X	X				X	X	X
Type of Model																
Multi-model														X	X	X
Time-series	X	X	X	X	X	X	X	X	X	X			NA	X		X
Causal	X							X	X	X	X	X	NA	X		X
Statistical						X	X	X	X	X	X	X	NA	X		X
Nonstatistical	X	X	X	X	X											X
Costs*																
Development	0	1	1	.5	4	4	1	8	3	6	8	10	0	5	9	9
Storage Requirements	3	1	1	0	7	7	0	7	6	8	9	10	2	7	5	NA
Running	NA	1	1	0	4	7	0	10	3	6	8	10	NA	[illegible]	7	[illegible]
Accuracy*																
Predicting Pattern	1	2	1	3.5	5	7	4	10	5	8	10	6	4	7	7	8
Predicting Turning Points	3.	0	0	0	3	6	0	8	0	1	6	0	5	7	8	[illegible]
Applicability*																
Time Required to Obtain Forecast	5	1	1	.5	3	4	1	7	2.5	6	9	10	0	3	6	[illegible]
Easiness to Understand and Interpret the Results	10	10	10	8	9	7	8	3	[illegible]	2	1	1	10	10	9	NA

*0 = smallest; 10 = highest.

CHAPTER III

METHODOLOGY

Overview

The overall objective of this research is determining if a multi-model forecasting strategy produces a more accurate demand forecast than the D062 system's current forecasting approach.

The specific methodology employed is:

1. Obtaining the actual demand data from AFLC.

2. Selecting and computerizing the models.

3. Using the actual demand data to generate demand forecasts from the various models.

4. Comparing the forecasting demands of several forecasting techniques against the actual demand to find the "best" model.

This chapter explains the details of the methodology. By following this methodology, the data analysis of the different forecasting methods can be made. The data analysis and results are presented in Chapter IV.

Data

The data consist of expendable line items from Oklahoma City and Sacramento Air Logistic Centers. The sample size is approximately 1480 line items.

This sample was picked using a stratified sampling approach. Only demand items from the D062 system were picked on a random basis by a program which skipped every four records. This sample was then stratified across the areas of unit cost, annual dollar amount, lead time, and weapon system.

Wholesale demand was used instead of retail demand data because of data availability, volume, and implementation. Wholesale data is easily accessible because AFLC's headquarters are located at Wright-Patterson AFB. AFLC/LORAA helped retrieve the data. The researchers decided to use wholesale demand data instead of retail demand data. The same analysis can be accomplished using a smaller quantity of wholesale data versus retail data. Also, wholesale demand data includes most of the information obtainable from retail data. Finally, this research will be more effective if it is implemented at the depot level where both wholesale and retail demand are affected.

In preparing the demand data, line items having 65 percent or more of their quarters with zero demand were eliminated from the analysis. Items having zero demand in a quarter means no demand occurred throughout the Air Force for that item in that particular quarter. The researchers decided to further eliminate line items by the following criteria:

1. Eliminate any items with less than three demands in the last sixteen quarters or four years.

2. Eliminate any items with less than six demands in the first eight years and less than two demands in the last two years.

If any line item has less than 65 percent of its quarters with zero demand it will not be eliminated even if the above criteria is met. By eliminating zero quantity demand quarters the analysis will not be offset by the amount of zeros contained in the data file. This elimination resulted in deleting 680 line items leaving 800 line items for analysis.

As mentioned in the previous chapter, the data have distinct underlying pattern distributions. The four types of patterns most frequently encountered are horizontal, seasonal, cyclical and trend demand patterns. A horizontal pattern, displayed in Figure 3-1, contains no trend in the data. Figure 3-2 shows a seasonal pattern exhibiting a series fluctuation according to some seasonal factor(s). Likewise, a cyclical pattern (Figure 3-3) exhibits seasonal tendencies but generally the length of a single cycle is longer than one year. Figure 3-4 displays a trend pattern which exhibits a general increase or decrease in the value of the variable over time.

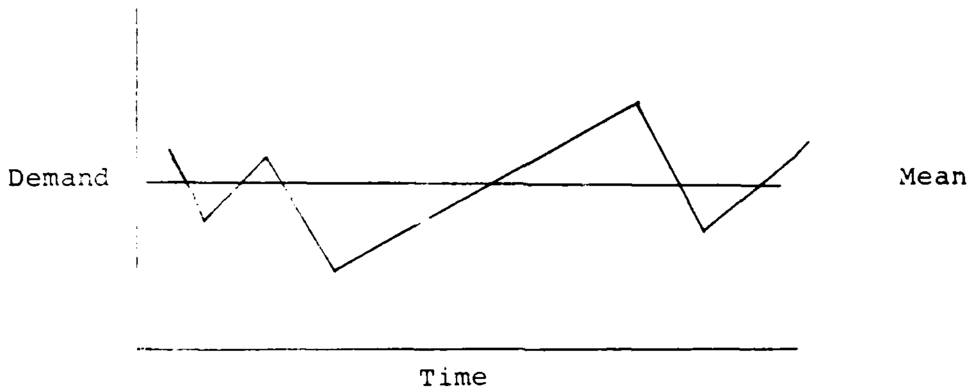

Fig. 3-1. Horizontal Demand Pattern

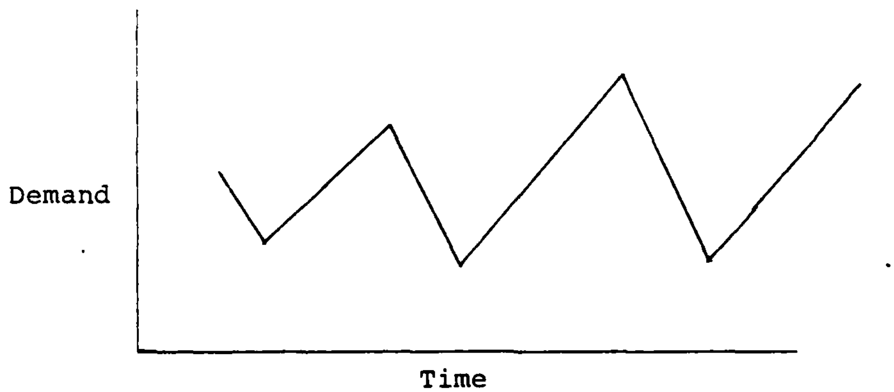

Fig. 3-2. Seasonal Demand Pattern

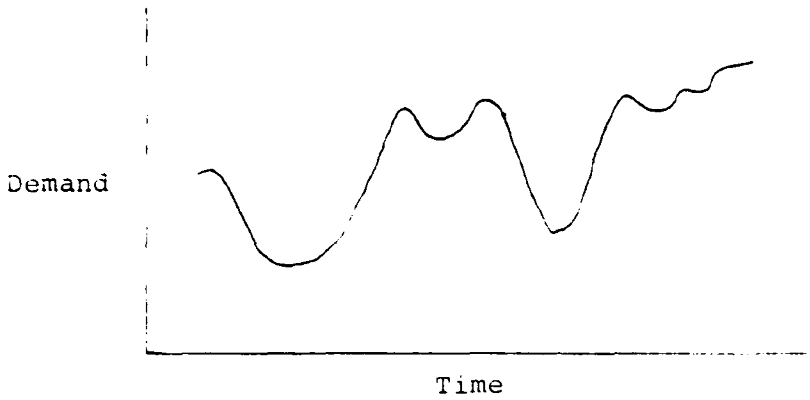

Fig. 3-3. Cyclical Demand Pattern

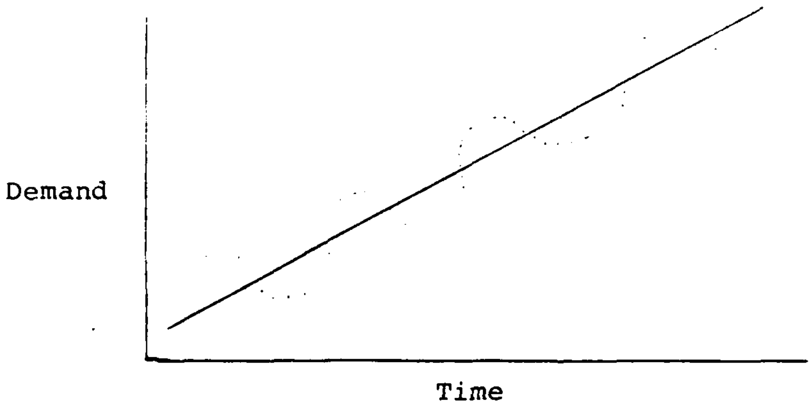

Fig. 3-4. Trend Demand Pattern

The data file exhibits a particular pattern or mixture of patterns. The specific pattern of data distribution determines the best forecasting technique. As the literature review points out, there are various techniques associated with distribution patterns. In selecting the forecasting models, these demand patterns were considered through statistical analysis and judgemental evaluation.

Models

The forecasting models were selected on the basis of information received in the literature review and an interactive forecasting approach, the SIBYL-RUNNER program (Makridakis, 1978).

The SIBYL-RUNNER program is an interactive for - casting system consisting of two sequential segments. The first segment, SIBYL, allows the user to perform a preliminary analysis of the input data for identification of the most appropriate techniques. The user at this point needs to consider all of the relevant factors surrounding a forecasting technique. These include time horizon, data pattern, accuracy, and availability. SIBYL analyzes the data and gives a listing of the recommended techniques. The user then has the option of using the second segment, RUNNER. RUNNER is composed of several subroutines which are computerized versions of common forecasting techniques.

The user selects a forecasting technique and the system runs the program. RUNNER then collects and summarizes the forecasting results.

The SIBYL program was used to identify appropriate techniques. Twenty to thirty items were randomly selected using a random number generator. Using the above approach, the SIBYL program identified three techniques. These are simple regression (SREG), S-curve analysis (SCURVE), and exponential growth modeling (EXGROW) (Makridakis, 1978: 120-127; 169-183).

In using the SIBYL program, the data displayed some distinct demand distributions. Figure 3-5 shows a S-curve distribution. Along with the S-curve, an exponential decay pattern is displayed in Figure 3-6. Although SIBYL recognized the above three techniques as being the most appropriate for the data file, the user needs to keep in mind that the SIBYL-RUNNER program is a preprogrammed analysis which needs to be used in conjunction with judgemental evaluation. Therefore, this research will explore the three techniques recommended by SIBYL; however, the literature review from Chapter II will serve as the basis for selection of additional techniques.

Based on the literature review the following techniques are incorporated into the analysis:

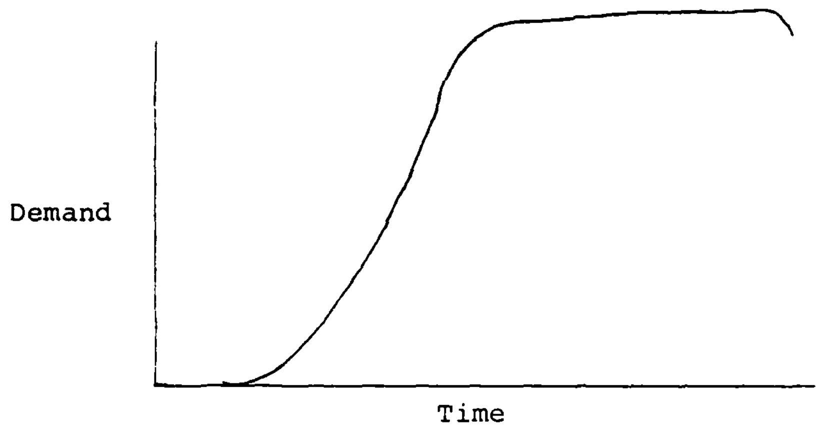

Fig. 3-5. S-Curve Demand Distribution

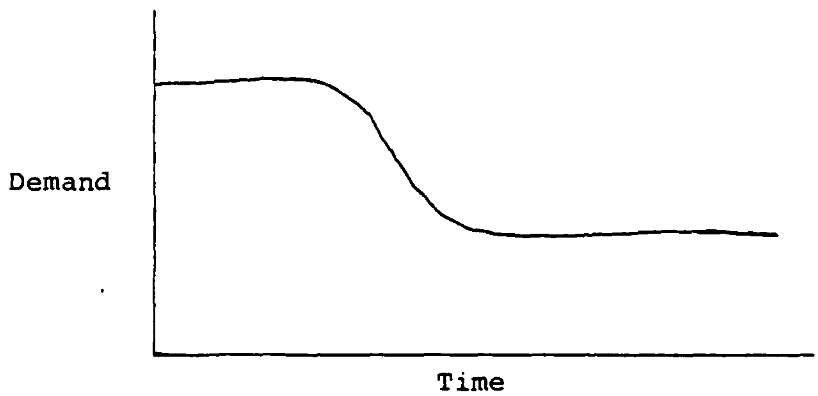

Fig. 3-6. Exponential Decay Pattern

1. Naive.

2. Simple Moving Average (4, 8, and 12 quarter). [Eight quarter is the present technique used by the D062 system.]

3. Double Moving Average (4, 8, and 12 quarter).

4. Single Exponential Smoothing.

5. Single Exponential Smoothing with trend.

6. Focus Forecasting.

7. Eclectic Forecasting.

The naive model forecasts demand for the following period using the most recent actual data. This model is used to get a rough comparison for use with the other sophisticated models.

$$F_{t+1} = D_t \tag{3.1}$$

where,

F_{t+1} = forecasted demand, and

D_2 = demand of present period.

[The formulas for the other forecasting models are contained in Chapter II and will not be repeated here.].

The simple moving average technique is used to "smooth" historical demand observations and eliminate randomness. The main assumption is the existence of several historical observations. AFLC's D062 system presently incorporates an eight-quarter simple moving average technique. The eight-quarter technique will be used along with the four-quarter and the twelve-quarter moving averages.

The double moving average operates in a manner similar to the simple moving average. Double moving average enables the moving average to respond better to trends, be more accurate, and overcome some of the drawbacks of the simple moving average. This research will analyze the four-quarter, eight-quarter, and twelve-quarter double moving average models.

Single exponential smoothing operates on the premise that the most recent demands experienced are more indicative of the future than are older demands. This is similar to the moving average except in the weighting of the observed demands. Adaptations of the model can easily be made to account for changing conditions. This is facilitated by altering the value of the weighting factor, alpha (α). The literature points out, an α of 0.1 gives a conservative forecast, while an α of 0.2 gives a more responsive system. Based on the recommendations found in the literature review, a single exponential smoothing model with a trend corrector will be analyzed using an α of 0.2 (Trigg, 1967:78). However, the research will also use an α of 0.8 just to determine the impact of the forecasting results on the model.

Focus forecasting is a multi-model technique which employs simplistic forecasting assumptions and computer simulation to forecast demand. The basic concept and simple strategies of focus forecasting are outlined in Chapter II. Focus forecasting will be analyzed along with the more complex technique of eclectic forecasting.

Eclectic forecasting is a technique incorporating two or more forecasting models in conjunction with computer simulation to forecast actual demand. Many computerized programs exist to analyze historical data and recommend several relevant forecasting techniques. The recommended techniques are similar to the recipe approach used in focus forecasting. However, the one important difference is eclectic forecasting incorporates more complex techniques than focus forecasting. Eclectic forecasting is the approach the researchers feel can more accurately forecast item demand. This is the process which heuristically determines the "most" appropriate technique.

The above techniques have been computerized for evaluation using the data. The researchers did an exhaustive search using the SIBYL program and the available literature. Both references suggest several good basic techniques. Every technique with the slightest possibility of application was included in the process. Using this selection procedure, the researchers are confident a thorough selection was accomplished. After selection of the techniques, the actual demand data will generate demand forecasts from the selected models. The generated forecasts are compared against the evaluation criteria to determine the "best" model.

Evaluation Criteria

In using forecasting models, it is important to be able to evaluate the performance of these models. Accuracy in a model is essential.

In this study, the accuracy of the forecasting models was measured using the Mean Absolute Deviation (MAD) and the tracking signal (TS). Accuracy is defined here as the closeness of the forecasted demand to the actual demand.

The MAD is computed using the differences between the actual demand and the forecasted demand without any regard to the sign (Chase and Aquilano, 1981:127). The MAD measures the average magnitude of the forecast error. It can be calculated as follows:

$$MAD = \frac{\sum_{t=1}^{n} |D_t - F_t|}{n} \tag{3.2}$$

where,

D_t = the actual demand for period t,

F_t = the forecasted demand for period t, and

n = the total number of periods computed in the study.

In general, the lower the value of the MAD, the better the accuracy of the model.

A type of analysis used on the MAD involves changing the mean absolute deviations to percentages. The "best" forecasting model is chosen as the standard for comparison. A visual analysis is performed on the MADs and tracking signals (discussed in the next section) to determine which is the "best" model. This model is used as the standard. For example, if the eclectic method is chosen as the "best" technique, the following computations are applicable:

1. The selected forecasting techniques excluding the eclectic forecast are considered at 100 percent.

2. The eclectic forecast mean absolute deviation is adjusted to a percentage using the ratio listed below:

$$\frac{\text{Other Selected Techniques}}{\text{Eclectic Forecast}} : \frac{100}{\text{Adjusted Eclectic}} \tag{3.3}$$

The statistical test, Oneway Analysis of Variance (ANOVA), is used to determine if a difference exists between the MADs of the forecasting techniques (FTM_i). The research hypothesis is:

H_0: $FTM_1 = FTM_2 \ldots FTM_x$;

H_A: At least one of the FTMs is different.

Another evaluation device, the tracking signal, is a measurement indicating whether the forecast average is keeping pace with real upward or downward changes in demand (Chase and Aquilano, 1981:127). A tracking signal is calculated using the arithmetic sum of forecast deviations (RSFE) divided by the mean absolute deviation (MAD).

Another point of interest in the analysis of forecasting models is the variance of the forecasts. The variance is very similar to the tracking signal in that it gives the range over which a forecast's result could vary. A high variance indicates that the model is unstable, while a low variance means the model is stable. Ideally, a variance of zero is desirable to make the forecasting model exact. The variance of a model is very important in a model's results, for if the forecast has a large variance and a low MAD, the forecast is no good since it has large fluctuations present. The variance (VAR) can be computed by the following equation:

$$VAR = \frac{\sum_{t=1}^{n} (D_t - F_t)^2}{n} \tag{3.4}$$

The above statistical tests will be used to evaluate the forecasts generated by each forecasting model and compared to the actual results. The subject of the next chapter is to provide the data analysis and results for the forecasting models.

CHAPTER IV

DATA RESULTS AND ANALYSIS

Introduction

The attainment of the objectives presented in Chapter I depend on the testing of the hypothesis: *A multi-model forecasting strategy produces a more accurate demand forecast than the present eight-quarter simple moving average used in the D062 inventory control system.*

The first objective was to study the appropriateness of various forecasting strategies for a sample of AFLC expendable items. This objective was accomplished by using a sample of 800 expendable items. Fifteen appropriate forecasting techniques were tested with this data. As mentioned in Chapter I, an exhaustive search was made using the SIBYL program and the available literature. The researchers feel all appropriate techniques for the expendable item data were included in the analytical process. The actual selection process was discussed in Chapter III.

The second objective involved developing and testing several time series forecasting models. This objective was successfully accomplished by developing fifteen applicable forecasting models. Each model was tested with the sample data and evaluated using the criteria defined in Chapter III.

The third objective was to determine if a more accurate forecasting strategy can be recommended for the present D062 system. Each forecasting strategy was analyzed for determination of the "best" technique. This chapter contains the results of the research analysis.

The appendix contains a listing of the computer program used by the researchers to incorporate the data with the forecasting models. Tracer switches and manual manipulation of the data provided verification of the program coding for the various forecasting techniques. A tracer switch is a technique incorporated into the program which allows certain key elements within the program to be printed out for verification when the switch is turned on. The researchers are satisfied with the results of the verification procedure.

This chapter provides the completed analysis and results of this research effort. Table 4-1 defines the model abbreviations used in this chapter and Chapter V.

Analysis

The analysis was performed using four strategies. The first strategy deals with writing a basic computer program incorporating the previously cited fourteen

TABLE 4-1

DEFINITION OF TERMS

NAV	=	naive
MA4	=	simple moving average using 4 periods
MA8	=	simple moving average using 8 periods
MA12	=	simple moving average using 12 periods
DMA4	=	double moving average using 4 periods
DMA8	=	double moving average using 8 periods
DMA12	=	double moving average using 12 periods
SES(.2)	=	single exponential smoothing with α of 0.2
SES(.8)	=	single exponential smoothing with α of 0.8
SES(T)	=	single exponential smoothing with trend
FF	=	focus forecasting
SREG	=	simple regression
SCURVE	=	S-curve analysis
EXGROW	=	exponential growth
ICLECT	=	eclectic method

Note: Further explanation of these forecasting techniques can be found in Chapter II.

forecasting techniques. The fifteenth technique, or eclectic method, was calculated using the previous period's "best" forecasting method for next period's forecast. The second strategy involves recoding the computer programs to change the calculation of a "mean percentage error" to incorporate the past three forecasting periods. Under this strategy the eclectic method is then calculated using the forecasting technique with the lowest "mean percentage error" over the past three periods. The calculation for the mean percentage error is a simple and straightforward approach. Each of the previous period's forecast was divided by the actual demand for the period. These results were added together to get an aggregate percentage. This was then divided by three to obtain an average percentage error. The average was subtracted from one and the absolute value of this number was used as the percentage error for the forecast. See the appendix for the computer program coding.

The third strategy uses the mean percentage error as the basic posture for the eclectic method's selection. The mean percentage error was calculated for all fourteen techniques, using the three techniques with the lowest values as weights in calculating the forecast for the eclectic method. The fourth strategy involved choosing the three forecasting techniques which consistently provided the "best" results in the first three strategies.

This strategy entailed recoding the computer program by dropping out the calculations for the other eleven techniques and thereby simplifying the process.

Table 4-2 summarizes the four strategies, the variations on those strategies, and gives the corresponding tables containing their results. Tables 4-3 to 4-9 are arranged in order of increasing Mean Absolute Deviation (MAD), with the lowest MAD being the "best" model. The Tracking Signal (TS) measures whether the forecast is keeping pace with any significant upward or downward changes in demand. The third statistic, the variance (VAR) is a measure of the range where a model's forecast value will fall. The fourth statistic, Mean Absolute Percentage (MA%) calculates the percentages of the MADs of all the forecasting techniques using the technique with the lowest MAD as the standard.

Strategy One

Table 4-3 contains aggregate performance statistics for the fifteen forecasting techniques. The eclectic method was calculated based on the immediately preceding period's "best" forecasting technique. Looking at the statistics in Table 4-3, the single exponential smoothing (SES(.2)) with an α of 0.2 and a MAD of 14.0 is ranked first. This means this model has the lowest

TABLE 4-2

SUMMARY OF ANALYSIS STRATEGIES

Strategy	Table	Explanation
1A	4-3	Incorporates all 15 techniques. Eclectic is calculated using previous period's best method for next period.
1B	4-4	Incorporates 12 techniques. Eclectic is calculated as in 1A.
2A	4-5	Incorporates 15 techniques. Uses the best of the last three periods for the next period forecast.
2B	4-6	Incorporates 12 techniques. Uses the same eclectic calculation as in 2A.
3	4-7	Incorporates 15 techniques. Uses the three techniques with lowest mean percentage error values as weights to calculate the eclectic method.
4A	4-8	Uses the three best techniques from the above strategies plus the naive and eclectic methods. Eclectic is calculated as in 1A.
4B	4-9	Uses the same techniques as in 4A and the same eclectic calculation as in 2A.

TABLE 4-3

STRATEGY 1A RESULTS

Model	MAD	TS	VAR	MA%
SES(.2)	14.0	7.5	7613	100.00
MA4	14.4	.9	8739	97.22
MA8	14.7	.16	8077	95.24
SES(.8)	15.1	2.1	9679	92.72
MA12	15.6	-2.6	7851	89.74
SES(T)	15.9	9.5	10761	88.05
DMA12	16.1	5.6	8477	86.96
MAV	16.2	-1.0	11246	86.42
DMA8	16.4	6.4	10082	85.37
DMA4	18.1	3.8	14008	77.35
FF	26.2	-7.6	136233	53.44
ICLECT	27.3	21.0	157476	51.28
EXGROW	32.6	20.1	---	42.94
SREG	94.4	23.7	---	14.83
SCURVE	2183.4	-22.9	---	.64

deviation from the actual demand. As is apparent, there are a number of models close to SES(.2). Simple moving average (4 and 8 period), and single exponential smoothing (α=0.8) have MADs of 14.4, 14.7 and 15.1, respectively. Also the small variance of SES(.2) means it is closest to the actual demand pattern in range. However, the tracking signals for MA4, MA8, and SES(.8) are better than SES(.2). Looking at the aggregate statistics, any of the models--SES(.2), MA4, MA8, and SES(.8)--could be the "best." It is interesting to note, focus forecasting and eclectic method did not perform well. They had MADs of 26.2 and 27.3, respectively. Also exponential growth, simple regression, and S-curve analysis had very large forecasting inaccuracies. The mean absolute percentages (MA%) with SES(.2) as the standard showed SES(.2) outperforming the eclectic method by 48.22 percent and focus forecasting by 46.56 percent. Again the top four techniques differ by only a slight percentage.

Table 4-4 contains the aggregate statistics for twelve forecasting techniques. The researchers decided to exclude exponential growth, simple regression, and S-curve analysis based on the statistics in Table 4-3. The researchers felt that the very high error rate exhibited by these three techniques may have in part induced a higher error rate for the eclectic method. Even though they had very high error rates the chances are, given the

TABLE 4-4

STRATEGY 1B RESULTS

Model	MAD	TS	VAR	MA%
SES(.2)	14.0	7.5	7613	100.00
MA4	14.4	.9	8739	97.22
MA8	14.7	.16	8077	95.25
SES(.8)	15.1	2.1	9679	92.72
MA12	15.6	-2.6	7851	89.74
SES(T)	15.9	9.5	10761	88.05
DMA12	16.1	5.6	8477	86.96
NAV	16.2	-1.0	11246	86.42
DMA8	16.4	6.4	10082	85.37
DMA4	18.1	3.8	14008	77.35
FF	26.2	-7.6	136233	53.44
ICLECT	27.6	21.0	157544	50.77

variability of the 800 ten year data streams, these techniques will at times be extremely accurate even if only through serendipity. It was felt that elimination of these outlying techniques would minimize such potential impact. The eclectic method is calculated the same as in the previous table. Again the results show SES(.2) as the "best" model followed closely by MA4, MA8, and SES(.8) (see Table 4-4). By excluding those three techniques--EXGROW, SREG, and SCURVE--the eclectic method did not improve its aggregate statistics. In fact, ICLECT shows up as the worst method. SES(.2) outperforms ICLECT by 49.28 percent.

Strategy Two

Table 4-5 shows the results for the fifteen forecasting techniques. SES(.2) leads the other techniques with a MAD of 14.0 and a VAR of 7613. MA4, MA8, and SES(.8) are close with MADs of 14.4, 14.7, and 15.1, respectively. The variances for the above techniques fall within a close range of each other. This suggests any of these four techniques could be the most appropriate technique. Recall that in strategy two, the eclectic method calculation chose the "best" performing technique over the past three periods and used it in the next period's forecast. Using this approach of calculating ICLECT, the MAD improved from 27.8 to 19.6. However, SES(.2) still

TABLE 4-5

STRATEGY 2A RESULTS

Model	MAD	TS	VAR	MA%
SES(.2)	14.0	7.5	7613	100.00
MA4	14.4	.9	8739	97.22
MA8	14.7	.16	8077	95.24
SES(.8)	15.1	2.1	9679	92.72
MA12	15.6	-2.6	7851	89.74
SES(T)	15.9	9.5	10761	88.05
DMA12	16.1	5.6	8477	86.96
NAV	16.2	-1.0	11246	86.42
DMA8	16.4	6.4	10082	85.37
DMA4	18.1	3.8	14008	77.35
ICLECT	19.6	2.2	118350	71.43
FF	26.2	-7.6	136233	53.44
EXGROW	32.6	20.1	---	42.94
SREG	94.4	23.7	---	14.83
SCURVE	2183.4	-22.9	---	.64

outperforms it by 28.57 percent. It is interesting to note NAV performs very close to some of the top forecasting techniques. NAV has an exceptionally good TS of -1.0 with a MAD of 16.2.

Table 6-4 deals with twelve forecasting techniques. Again EXGROW, SREG, nd SCURVE were excluded for the same reasons as before. ECLECT does not show significant improvement from Table 4-5's results. SES(.2) still outperforms ECLECT by 29.29 percent.

Strategy Three

Table 4-7 contains aggregate statistics for the fifteen forecasting strategies calculated via strategy three. The eclectic forecasting technique was arrived at by using the mean performance error. The mean percentage error was calculated for each forecasting technique and those results were used in a weighting technique to arrive at the eclectic forecast.

This weighting technique was used to calculate a new value for the eclectic forecast versus selecting one of the other forecasting techniques and using that technique's forecast. The technique developed represents an extension of Granger and Newbold's work (Granger and Newbold, 1979: 269). The weights were developed in five steps.

1. Add the forecast of those three techniques which had performed closest to the actual demand.

TABLE 4-6

STRATEGY 2B RESULTS

Model	MAD	TS	VAR	MA%
SES(.2)	14.0	7.5	7613	100.00
MA4	14.4	.7	8739	97.22
MA8	14.7	.16	8077	95.24
SES(.8)	15.1	2.1	[illegible]	92.72
MA12	15.6	-2.6	7851	89.74
SES(T)	15.9	9.5	10761	88.05
DMA12	16.1	5.6	8477	86.96
NAV	16.2	-1.0	11246	86.42
DMA8	16.4	6.4	10082	85.37
DMA4	18.1	3.8	14008	77.35
ICLECT	19.8	.7	118354	70.71
FF	26.2	-7.6	136233	53.44

TABLE 4-7

STRATEGY 3 RESULTS

Model	MAD	TS	VAR	MA%
SES(.2)	14.0	7.5	7613	100.00
MA4	14.4	.9	8739	97.22
MA8	14.7	.16	8077	95.24
SES(.8)	15.1	2.1	9679	92.72
MA12	15.6	-2.6	7851	89.74
SES(T)	15.9	9.5	10761	88.05
DMA12	16.1	5.6	8477	86.96
NAV	16.2	-1.0	11246	86.42
ICLECT	16.3	5.0	30123	85.89
DMA8	16.4	6.4	10082	85.37
DMA4	18.1	3.8	14008	77.35
FF	26.2	-7.6	136233	53.44
EXGROW	32.6	20.1	---	42.94
SREG	94.4	23.7	---	14.85
SCURVE	2183.4	-22.9	---	.64

2. Calculate percentage values by using the above total as the divisor and the individual forecasts as the dividend.

3. Invert these percentages--subtract them from one--to normalize the weights.

4. Add these normalized values and divide by the total to get the final weights.

5. Compute the eclectic forecast by using these weights.

An example of the above weighting technique follows:

T[illegible]osest forecast values

[illegible]	forecast 1
50	forecast 2
30	forecast 3
100	total

Percentage calculations

20/100 = .2

50/100 = .5

30/100 = .3

Inverted values

1 - .2 = .8

1 - .5 = .5

1 - .3 = .7

2.0

Final weights

$$.8/2 = .4; \; .5/2 = .25; \; .7/2 = .35$$

Eclectic computation

$$ICLECT = (.4*20) + (.25*50) + (.35*30)$$

$$ICLECT = 8 + 12.5 + 10.5$$

$$ICLECT = 30$$

Once again the SES(.2) forecasting technique outperforms the others. The eclectic method has a MAD of 16.3 and a TS of 5.6 which represents further improvement but its performance only now approximately equals that of the naive method (i.e., expect next period to be the same as this period). The SES(.2) method is still 14.11 percent better than the eclectic method.

Strategy Four

Tables 4-8 and 4-9 represent the results of implementing the fourth strategy. The five forecasting techniques used were the three techniques which performed the "best" during the execution of the other strategies. The fourth technique was the eclectic method. The naive technique is included merely as a reference point and was not used in calculating the eclectic model results. Referring to Table 4-7, the researchers limited this strategy to SES(.2), MA4, and MA8. The fourth "best" technique, SES(.8), was not chosen because of its close similarity with SES(.2). The only difference is the alpha value of 0.8 instead of 0.2. The fifth "best" technique, MA12, is another simple moving average technique using 12 periods. This technique was eliminated because MA4 and MA8 had significantly lower MADs than MA12. The rest of the techniques clearly do not come close to the top three.

Table 4-8 presents the results using the eclectic forecast calculation of selecting the previous period's "best" forecasting method for next period's forecast. As expected, all the statistics remained the same except for the eclectic method. The MAD for the eclectic method is 31.5 with a TS of 8.92. The SES(.2) forecasting technique is still 55.56 percent better.

Table 4-9 contains the results of using the four techniques with the eclectic method calculated as in strategy two. The MAD for the eclectic method is 14.3 with a TS of 3.15. The SES(.2) technique is 2.1 percent better than the eclectic method.

After obtaining the results of the previously mentioned strategies the Oneway Analysis of Variance (ANOVA) test was used to determine if a difference exists between the MADs of the forecasting techniques (FTM_i). As mentioned in Chapter III, the research hypothesis is:

H_0: $FTM_1 = FTM_2 \ldots FTM_x$;

H_A: At least one of the FTM_i's is different.

TABLE 4-8

STRATEGY 4A RESULTS

Model	MAD	TS	VAR	MA%
SES(.2)	14.0	7.5	7613	100.00
MA4	14.4	.9	8739	97.22
MA8	14.7	.16	8077	95.23
NAV	16.2	-1.0	11246	86.42
ICLECT	31.5	8.92	140624	44.44

TABLE 4-9

STRATEGY 4B RESULTS

Model	MAD	TS	VAR	MA%
SES(.2)	14.0	7.5	7613	100.00
ICLECT	14.3	3.15	8652	97.90
MA4	14.4	.9	8739	97.22
MA8	14.7	.16	8077	95.23
NAV	16.2	-1.0	11246	86.42

Table 4-10 gives the results of the ANOVA tests. This table is set up to show the different subsets of homogenous groups within each strategy. Homogenous subsets are subsets of groups whose highest and lowest means do not differ by more than the shortest significant range for a subset of that size. The level of significance for the Duncan range test is 0.05.

The ANOVA results failed to show any significant difference between the ICLECT method and the top twelve techniques at a 0.05 significance level. SREG and SCURVE were different but their MADs were extremely large.

Summary

The results show simple exponential smoothing with an α of 0.2 as the forecasting model with lowest MAD and variance. Likewise, the techniques of simple moving average (4 and 8 period) and simple exponential smoothing (α=0.8) exhibited very similar results. The ANOVA test showed no significant difference between the eclectic method and the top twelve techniques. However, from the other test results, the eclectic method and focus forecasting performed somewhat inferior for the data tested. Chapter V further elaborates on the conclusions and makes recommendations on future actions.

TABLE 4-10

ONEWAY ANALYSIS OF VARIANCE RESULTS

Strategy	Results
1A	<u>Subset I</u> NAV, MA4, MA8, MA12, DMA4, DMA8, DMA12, SES(.2), SES(.8), SES(T), ICLECT, FF, EXGROW <u>Subset II</u> SREG <u>Subset III</u> SCURVE
1B	<u>Subset I</u> NAV, MA4, MA8, MA12, DMA4, DMA8, DMA12, SES(.2), SES(.8), SES(T), ICLECT, FF
2A	<u>Subset I</u> NAV, MA4, MA8, MA12, DMA4, DMA8, DMA12, SES(.2), SES(.8), SES(T), ICLECT, FF, EXGROW <u>Subset II</u> SREG <u>Subset III</u> SCURVE
2B	<u>Subset I</u> NAV, MA4, MA8, MA12, DMA4, DMA8, DMA12, SES(.2), SES(.8), SES(T), ICLECT, FF
3	<u>Subset I</u> NAV, MA4, MA8, MA12, DMA4, DMA8, DMA12, SES(.2), SES(.8), SES(T), ICLECT, FF, EXGROW <u>Subset II</u> SREG <u>Subset III</u> SCURVE

TABLE 4-10--Continued

Strategy	Results
4A	Subset I SES(.2), MA4, MA8, ICLECT, NAV
4B	Subset I SES(.2), MA4, MA8, ICLECT, NAV

CHAPTER V

CONCLUSIONS AND RECOMMENDATIONS

The research question addressed in this study was: *Can a multi-model forecasting strategy produce a more accurate demand forecast than the present eight-quarter simple moving average technique used in the D062 inventory control system?*

Conclusions

The results of this research indicate a multi-model forecasting strategy is not likely to produce a more accurate demand forecast for the D062 system. The data analysis results suggest several conclusions which correlate with the objectives of this research.

Objective One

The first objective was to study the appropriateness of various forecasting techniques for a sample of AFLC expendable items. The analysis of the data was performed using visual analysis, manual manipulation, and computer diagnosis via the SIBYL/RUNNER programs (Makridakis, 1978). The data structure uncovered during this analysis showed some normal demand patterns with considerable random variation.

Of primary importance within this analysis was the discovery of a high number of item stock numbers exhibiting zero demand for the past 38 quarters (1972-1981). Approximately 46 percent--680 out of 1480--of the stratified random sampled items were virtually zero demand. The researchers tried to pursue this matter further with AFLC/LORAA and had no success. Although the researchers found some items with zero demand and quantities on order, AFLC/LORAA implied the data "on order" figures were the initial estimates for fiscal years 1971-72 and were not representative of current requirements. However, the item record as of 1981 still shows the "on order" quantities. The current figures for these items were unavailable for comparative purposes. It is important to determine the amount of zero demand items contained in an automated inventory control program. A significant percentage of such items could impair the results of any time series forecasting technique. In essence, very sparse demand data tends to distort the validity of the forecasting techniques. The researchers decided to eliminate zero demand type data using the criteria defined in Chapter III. Deleting zero demand items brings up the question of excluding those items from automated inventory systems. This is a question not answered by this research but it conveys an interesting point. Could cost savings be achieved if zero demand items were excluded from the automated inventory system? Should decisions regarding their management be made through other more appropriate techniques? What are the data system costs associated with the current inclusion of these sparse demand items?

In addition, the data analysis provided some initial insight into the random fluctuations of the actual demand data. The SIBYL/RUNNER program suggested complex forecasting techniques which consistently proved least reliable in forecasting ability. These results, outlined in Chapter IV, indicate the SIBYL program, a preprogrammed technique, did not work well. This appears to be due to the simplistic program logic built into the preprogrammed techniques. However, the SIBYL program was useful in that it indicated the data does not exhibit the pure, normal demand patterns. The researchers therefore inferred a fairly high degree of randomness is present in the data.

Objective Two

The second objective involves developing and testing several forecasting models which are feasible for use with the data. An exhaustive analysis was performed to insure any forecasting model with the slightest chance of applicability was included in the study. This was accomplished both quantitatively and qualitatively. Quantitatively, the forecasting technique selection was made using visual analysis and the SIBYL/RUNNER programs. Qualitatively, the techniques were selected from a complex and detailed literature review. The fifteen techniques selected are listed in Table 4-1.

Objective Three

The third objective was to determine if a more accurate forecasting technique could be recommended for the present D062 system. This objective also dealt with determining if a multi-model method was the most feasible technique. This research employed four comprehensive strategies outlined in Table 4-2. Each of the four strategies employs a different approach to the eclectic method calculation. The first strategy uses the previous period's "best" method to forecast the next period's demand. However, the researchers felt this approach was being degraded because even the worst techniques could get lucky and come up as the "best" predictor for a given period. Therefore, strategy two uses the "best" method over the last three periods for the next period's forecast. In an effort to come up with a still more effective approach, the third strategy employs weighting the techniques with the lowest mean percentage error values. A considerable improvement was seen in the MAD value of the eclectic method. The final strategy involves taking the three best techniques from the above strategy results and using them along with the eclectic method as calculated in the first strategy. The results from these strategies (Tables 4-3 to 4-9) did not show the multi-model methods--focus forecasting or eclectic--as the most effective predictors of the next period's actual demand. The "best" forecasting technique in all four strategies for this sample of data was the single exponential smoothing model with an α of 0.2. This technique had the lowest MAD of 14.0, a TS of 7.5, and a variance of 7613. Although it did not track the actual demand data as well as other techniques, it did have the lowest variance. The four and eight period single moving average forecasting techniques performed almost as well as single exponential smoothing (α=0.2) and can not be considered statistically different.

Recommendations

A final objective of this research is recommending further actions based upon the results of this analysis. The following recommendations are considered important to further evaluate the results and to extend the scope of this thesis.

1. Additional research is required to investigate the high level of item stock numbers with zero demand. Almost 46 percent of the stratified random sample received for this study exhibited zero demand. A different type of inventory control such as an ABC type technique, might provide lower costs and a simpler inventory control system. The ABC technique divides inventory items into areas such

as: high dollar volume (A), moderate dollar volume (B), and low dollar volume (C). Classifying items into areas makes it easier to establish the appropriate degree of control over each item (Chase and Aquilano, 1981:490-491).

2. The focus forecasting technique did not perform well. This technique is reputed to have significant merit when demand is generated outside the system, such as in forecasting end-item demand, spare parts, and materials and supplies used in a variety of products (Smith, 1978:203-209). The expendable line item data used in this research were of the above type and focus forecasting was expected to have performed well with this data. Further analysis of this technique is required since this research clearly refutes Smith's hypothesis (1978:1-4).

3. The eclectic forecasting technique needs further testing. This study provided extensive initial investigation into this technique using a large data base, but more research is needed. Data with more conventional demand distributions or with less randomness should be analyzed. Different criteria for making the eclectic selection might also be established. The above recommendations should help develop eclectic forecasting techniques and improve their forecasting accuracy and reliability.

4. Since the single exponential smoothing technique with an α of 0.2 consistently achieved the minimum

MAD, AFLC should consider introducing it to the D062 system. The final decision must consider the cost of conversion and lower data processing costs associated with the single exponential smoothing technique. Also, AFLC needs to consider the fact that the current system did exhibit the smallest tracking signal for the data sample.

Summary

This research focuses on determining if a multimodel forecasting strategy can more accurately predict item demand. Using ten years of actual expendable (nonrecoverable) data, the analysis tested the following forecasting techniques: naive, simple moving average (4, 8, and 12 periods), double moving average (4, 8, and 12 periods), single exponential smoothing (α of 0.2 and 0.8), single exponential smoothing with trend, focus forecasting, simple regression, S-curve analysis, exponential growth and the eclectic method. The forecasting technique's results are compared in terms of mean absolute deviation and percentage change, tracking signal, and variance. The statistical test, Oneway Analysis of Variance, tests for significant differences between the techniques. Although simple exponential smoothing (α=0.2) has the lowest MAD and variance, several techniques exhibit similar results. The ANOVA test results show no significant difference between the eclectic method and the top twelve techniques. This

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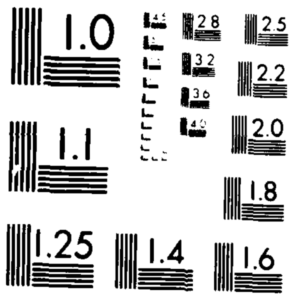

MICROCOPY RESOLUTION TEST CHART

further supports the conclusion that the simple exponential smoothing technique does not stand out clearly as the "best" technique. Hopefully, the stated recommendations will be pursued.

APPENDIX

PROGRAM LISTING

```
      PROGRAM MAIN
      REAL LC,RIFRPR,RCNT(14,2),IMAD(15),SPE(15),TSIGS(15),
     +AVMAD(15),AVE(15),VAR(15),AVTRS(15),AVVAR(15)
      INTEGER FSC,MIING,MIINI,ECODE,ICHA,ICOU,ALT,PLT,IPLT
      INTEGER ACTUAL(38)
      INTEGER NAIVE(38),MA4(38),MA8(38),MA12(38),DMA4(38),DMA8(38)
      INTEGER DMA12(38),SESNOT2(38),SESNOT3(38),DESTRND(38),DESTRND(38)
      INTEGER FF(38),FF1(38),FF2(38),FF3(38),FF4(38),FF5(38)
      INTEGER IFEG(38),ICOUNT(38),IERROR(38),IQUIT(38)
      CHARACTER ALC*2,MMC*2,LT*2,[illegible]
      OPEN(15,FILE='THESIS')
      REWIND 15
      REWIND 20
      NRECNTR = 0
      DO 2 I = 1,15
         AVMAD(I) = 0.0
         AVTRS(I) = 0.0
         AVVAR(I) = 0.0
2     CONTINUE
      IQUIT = 0
20    IF (IQUIT .EQ. [illegible]) GO TO 999
      IQUIT = IQUIT + 1
      READ(15,50,END=999) ALC,MMC,FSC,MIING,MIINI,[illegible]
     +ECODE,SMG,WSCODE,TCC
50    FORMAT(A2,1X,A2,1X,I4,1X,I6,1X,I7,1X,A2,1X,F7.2,[illegible]
     +I1,1X,A1,1X,A4,1X,A1)
      READ(15,55,END=999) ICHA,ICOU,ALT,PLT,IPLT,RIFRPR
55    FORMAT(1X,I7,1X,I7,1X,I7,1X,I7,1X,I7,1X,F2.0)
      READ(15,*,END=999) (ACTUAL(J),J=1,38)
*************************************************************************
C     THE FOLLOWING CODE CALCULATES THE NAIVE FORECAST
*************************************************************************
      DO 100 I = 1,37
         NAIVE(I+1) = ACTUAL(I)
100   CONTINUE
*************************************************************************
C     THIS ROUTINE CALCULATES THE SINGLE MOVING AVERAGE FORECASTS
C     THIS INCLUDES A 4, 8, AND 12 PERIOD MOVING AVERAGE.
*************************************************************************
C     4-PERIOD MOVING AVERAGE
      DO 200 I = 1,4
         MA4(I) = ACTUAL(I)
200   CONTINUE
      DO 210 I = 5,38
         MA4(I) = (ACTUAL(I-4) + ACTUAL(I-3) + ACTUAL(I-2) + ACTUAL(I-1)
     +)/ 4.0
210   CONTINUE
C     8-PERIOD MOVING AVERAGE
      DO 220 I = 1,8
         MA8(I) = ACTUAL(I)
```

```
220    CONTINUE
       DO 230 I = 9,38
          MA8(I) = (ACTUAL(I-8)+ACTUAL(I-7)+ACTUAL(I-6)+ACTUAL(I-5)+
      +ACTUAL(I-4)+ACTUAL(I-3)+ACTUAL(I-2)+ACTUAL(I-1)) / 8.0
230     CONTINUE
C      12 PERIOD MOVING AVERAGE
       DO 240 I = 1,12
          MA12(I) = ACTUAL(I)
240    CONTINUE
       DO 250 I = 13,38
          MA12(I) = (ACTUAL(I-12)+ACTUAL(I-11)+ACTUAL(I-10)+ACTUAL(I-9)+
      +ACTUAL(I-8)+ACTUAL(I-7)+ACTUAL(I-6)+ACTUAL(I-5)+ACTUAL(I-4)+
      +ACTUAL(I-3)+ACTUAL(I-2)+ACTUAL(I-1)) / 12.0
250    CONTINUE
*************************************************************************
C      THE FOLLOWING CODE CONTINUES WITH THE DOUBLE MOVING AVERAGE
C      FOR 4, 8, AND 12 PERIODS.
*************************************************************************
C      4-PERIOD DOUBLE MOVING AVERAGE
       DO 260 I = 1,4
          DMA4(I) = ACTUAL(I)
260    CONTINUE
       DO 265 I = 5,38
          FDPRIMT = (MA4(I) + MA4(I-1) + MA4(I-2) + MA4(I-3)) / 4.0
          ASUBT = 2 * MA4(I) - FDPRIMT
          BSUBT = (2.0 / 3.0) * (MA4(I) - FDPRIMT)
          DMA4(I) = ASUBT + BSUBT
265    CONTINUE
C      8-PERIOD DOUBLE MOVING AVERAGE
       DO 270 I = 1,8
          DMA8(I) =  ACTUAL(I)
270    CONTINUE
       DO 275 I = 9,38
          FDPRIMT = (MA8(I) + MA8(I-1) + MA8(I-2) + MA8(I-3) +
      +MA8(I-4) + MA8(I-5) + MA8(I-6) + MA8(I-7)) / 8.0
          ASUBT = 2 * MA8(I) - FDPRIMT
          BSUBT = (2.0/7.0) * (MA8(I) - FDPRIMT)
          DMA8(I) = ASUBT + BSUBT
275    CONTINUE
C      12-PERIOD DOUBLE MOVING AVERAGE
       DO 280 I = 1,12
          DMA12(I) = ACTUAL(I)
280    CONTINUE
       DO 285 I = 13,38
          FDPRIMT = (MA12(I) + MA12(I-1) + MA12(I-2) + MA12(I-3) +
      +MA12(I-4) + MA12(I-5) + MA12(I-6) + MA12(I-7) +
      +MA12(I-8) + MA12(I-9) + MA12(I-10) + MA12(I-11)) / 12.0
          ASUBT = 2 * MA12(I) - FDPRIMT
          BSUBT = (2.0 / 11.0) * (MA12(I) - FDPRIMT)
          DMA12(I) = ASUBT + BSUBT
```

```
235   CONTINUE
************************************************************************
C     THIS ROUTINE CALULATES THE SINGLE EXPONENTIAL SMOOTHING
************************************************************************
C     ALPHA OF .2 WITHOUT TREND
      SESNOT2(1) = 0
      DO 320 I = 2,38
         SESNOT2(I) = (.2 * ACTUAL(I-1)) +(.8 * SESNOT2(I-1))
320   CONTINUE
C     ALPHA OF .3 WITHOUT TREND
      SESNOT3(1) = 0
      DO 330 I = 2,38
         SESNOT3(I) = (.3 * ACTUAL(I-1)) + (.2 * SESNOT3(I-1))
330   CONTINUE
C     ALPHA OF .2 WITH TREND
C     BETA OF .3
      SESTRND(1)=SESTRND(2) = 0
      TREND1 =  0.0
      DO 340 I = 3,38
         TREND = .3 * (SESTRND(I-1) - SESTRND(I-2)) + .7 * TREND1
         SESTRND (I) = .2 * ACTUAL(I-1) + .8 * (SESTRND(I-1) + TREND)
      TREND1 = TREND
340   CONTINUE
************************************************************************
C     THE FOLLOWING CODE DETERMINES THE FOCUS FORECASTING VALUES
************************************************************************
      DO 420 I = 1,8
         FF(I) = ACTUAL(I)
420   CONTINUE
      DO 430 I = 9,38
         FF1(I) = ACTUAL(I-1)
         FF2(I) = ACTUAL(I-4)
         FF3(I) = ACTUAL(I-1) * 1.10
         FF4(I) = ACTUAL(I-4) * 1.50
           DIFF = ABS(ACTUAL(I-3) - ACTUAL(I-4))
         IF (ACTUAL(I-4) .LT. 1) THEN
            PERCNT = DIFF / 1
         ELSE
           PERCNT = DIFF / ACTUAL(I-4)
         ENDIF
           IF (ACTUAL(I-4) .LT. ACTUAL(I-3)) THEN
              FF5(I) = ACTUAL(I-1) * (1.0 + PERCNT)
           ELSE
              FF5(I) = ACTUAL(I-1) * (1.0 - PERCNT)
         ENDIF
430   CONTINUE
      DO 440 I = 9,38
         IF (ACTUAL(I-1) .LT. 1.0) THEN
            ACTI1 = 1.0
         ELSE
```

```
            ACTI1 = ACTUAL(I-1)
         ENDIF
         IF (ACTUAL(I-2) .LT. 1.0)  THEN
            ACTI2 = 1.0
         ELSE
            ACTI2 = ACTUAL(I-2)
         ENDIF
         IF (ACTUAL(I-3) .LT. 1.0) THEN
            ACTI3 = 1.0
         ELSE
            ACTI3 = ACTUAL(I-3)
         ENDIF
         PERCNT1 = ABS(1.0 - (((FF1(I-3)/ACTI3) +
     + (FF1(I-2)/ACTI2) +
     + (FF1(I-1)/ACTI1)) / 3.0))
         PERCNT2 = ABS(1.0 - (((FF2(I-3)/ACTI3) +
     + (FF2(I-2)/ACTI2) +
     + (FF2(I-1)/ACTI1)) / 3.0))
         PERCNT3 = ABS(1.0 - (((FF3(I-3)/ACTI3) +
     + (FF3(I-2)/ACTI2) +
     + (FF3(I-1)/ACTI1)) / 3.0))
         PERCNT4 = ABS(1.0 - (((FF4(I-3)/ACTI3) +
     + (FF4(I-2)/ACTI2) +
     + (FF4(I-1)/ACTI1)) / 3.0))
         PERCNT5 = ABS(1.0 - (((FF5(I-3)/ACTI3) +
     + (FF5(I-2)/ACTI2) +
     + (FF5(I-1)/ACTI1)) / 3.0))
         IF ((PERCNT1 .LE. PERCNT2) .AND. (PERCNT1 .LE. PERCNT3) .AND.
     + (PERCNT1 .LE. PERCNT4) .AND. (PERCNT1 .LE. PERCNT5))
     +FF(I) = FF1(I)
         IF ((PERCNT2 .LE. PERCNT1) .AND. (PERCNT2 .LE. PERCNT3) .AND.
     +(PERCNT2 .LE. PERCNT4) .AND. (PERCNT2 .LE. PERCNT5))
     +FF(I) = FF2(I)
         IF ((PERCNT3 .LE. PERCNT1) .AND. (PERCNT3 .LE. PERCNT2) .AND.
     +(PERCNT3 .LE. PERCNT4) .AND. (PERCNT3 .LT. PERCNT5))
     +FF(I) = FF3(I)
         IF ((PERCNT4 .LE. PERCNT1) .AND. (PERCNT4 .LE. PERCNT2) .AND.
     +(PERCNT4 .LE. PERCNT3) .AND. (PERCNT4 .LE. PERCNT5))
     +FF(I) = FF4(I)
         IF ((PERCNT5 .LE. PERCNT1) .AND. (PERCNT5 .LE. PERCNT2) .AND.
     +(PERCNT5 .LE. PERCNT3) .AND. (PERCNT5 .LE. PERCNT4))
     +FF(I) = FF5(I)
440   CONTINUE
***********************************************************************
C     THE FOLLOWING CODE GENERATES THE S-CURVE, EXPONENTIAL GROWTH, AND
C     THE SIMPLE REGRESSION FORECASTS.
***********************************************************************
      DO 450 I = 1,9
         SREG(I) = ACTUAL(I)
         SCURVE(I) = ACTUAL(I)
```

```
          S(GROW(I) = ACTUAL(I)
 45     CONTINUE
        DO 460 N = 9,23
          SUMTX=SUMT=SUMT2=SUMX=0.0
          DO 455   = 1,N-1
             SUMTX = SUMTX + [illegible] ACTUAL( )
             SUMT = SUMT + K
             SUMT2 = SUMT2 + K ** 2
             SUMX = SUMX + ACTUAL(K)
 455      CONTINUE
          SLOPE = [illegible]
          INTRCPT = [illegible] SLOPE * [illegible]
          PRED( ) = INTRCPT + SLOPE [illegible]
          UNFLD = PRED(N)
          IF UNFLD .LT. [illegible]
          S(GROW(N) = 2.71828 ** [illegible]
          IF (SLOPE .GE. [illegible] SLOPE = [illegible]
          VRFLD = INTRCPT + SLOPE [illegible]
          IF ( RFLD .GT. 9.0) VRFLD = 8.
          SCURVE(N) = 2.71828 ** VRFLD
 46     CONTINUE
*******************************************************************************
        THIS ROUTINE CALCULATES THE [illegible]
C       WHEN THE STRATEGY IS TO SELECT THE [illegible]
C       MEAN FOR THE LAST THREE MONTHS.
*******************************************************************************
        DO 500 I = 1,8
          ICLSCT(I) = ACTUAL(I)
 5      CONTINUE
        DO 510 I = 9,23
          IF(ACTUAL(I-1) .LT. 1.0) THEN
             ACTI1 = 1.0
          ELSE
             ACTI1 = ACTUAL(I-1)
          ENDIF
          IF (ACTUAL(I-2) .LT. 1.0) THEN
             ACTI2 = 1.0
          ELSE
             ACTI2 = ACTUAL(I-2)
          ENDIF
          IF (ACTUAL(I-3) .LT. 1.0) THEN
             ACTI3 = 1.0
          ELSE
             ACTI3 = ACTUAL(I-3)
          ENDIF
          PCNT(1,1) = ABS(1.0 - (((NAIVE(I-3)/ACTI3) +
     +                (NAIVE(I-2)/ACTI2) +
     +                (NAIVE(I-1)/ACTI1)) / 3.0))
          PCNT(1,2) = NAIVE(I)
          PCNT(2,1) = ABS(1.0 - (((MA4(I-3)/ACTI3) +
```

```
     +              (MA4(I-2)/ACTI2) +
     +              (MA4(I-1)/ACTI1)) / 3.0))
      PCNT(2,2) = MA4(I)
      PCNT(3,1) = ABS(1.0 - (((MA8(I-3)/ACTI3) +
     +              (MA8(I-2)/ACTI2) +
     +              (MA8(I-1)/ACTI1)) / 3.0))
      PCNT(3,2) = MA8(I)
      PCNT(4,1) = ABS(1.0 - (((MA12(I-3)/ACTI3) +
     +              (MA12(I-2)/ACTI2) +
     +              (MA12(I-1)/ACTI1)) / 3.0))
      PCNT(4,2) = MA12(I)
      PCNT(5,1) = ABS(1.0 - (((DMA4(I-3)/ACTI3) +
     +              (DMA4(I-2)/ACTI2) +
     +              (DMA4(I-1)/ACTI1)) / 3.0))
      PCNT(5,2) = DMA4(I)
      PCNT(6,1) = ABS(1.0 - (((DMA8(I-3)/ACTI3) +
     +              (DMA8(I-2)/ACTI2) +
     +              (DMA8(I-1)/ACTI1)) / 3.0))
      PCNT(6,2) = DMA8(I)
      PCNT(7,1) = ABS(1.0 - (((DMA12(I-3)/ACTI3) +
     +              (DMA12(I-2)/ACTI2) +
     +              (DMA12(I-1)/ACTI1)) / 3.0))
      PCNT(7,2) = DMA12(I)
      PCNT(8,1) = ABS(1.0 - (((SESNOT2(I-3)/ACTI3) +
     +              (SESNOT2(I-2)/ACTI2) +
     +              (SESNOT2(I-1)/ACTI1)) / 3.0))
      PCNT(8,2) = SESNOT2(I)
      PCNT(9,1) = ABS(1.0 - (((SESNOT8(I-3)/ACTI3) +
     +              (SESNOT8(I-2)/ACTI2) +
     +              (SESNOT8(I-1)/ACTI1)) / 3.0))
      PCNT(9,2) = SESNOT8(I)
      PCNT(10,1) = ABS(1.0 - (((SESTRND(I-3)/ACTI3) +
     +              (SESTRND(I-2)/ACTI2) +
     +              (SESTRND(I-1)/ACTI1)) / 3.0))
      PCNT(10,2) = SESTRND(I)
      PCNT(11,1) = ABS(1.0 - (((FF(I-3)/ACTI3) +
     +              (FF(I-2)/ACTI2) +
     +              (FF(I-1)/ACTI1)) / 3.0))
      PCNT(11,2) = FF(I)
      PCNT(12,1) = ABS(1.0 - (((SREG(I-3)/ACTI3) +
     +              (SREG(I-2)/ACTI2) +
     +              (SREG(I-1)/ACTI1)) / 3.0))
      PCNT(12,2) = SREG(I)
      PCNT(13,1) = ABS(1.0 - (((SCURVE(I-3)/ACTI3) +
     +              (SCURVE(I-2)/ACTI2) +
     +              (SCURVE(I-1)/ACTI1)) / 3.0))
      PCNT(13,2) = SCURVE(I)
      PCNT(14,1) = ABS(1.0 - (((EXGROW(I-3)/ACTI3) +
     +              (EXGROW(I-2)/ACTI2) +
     +              (EXGROW(I-1)/ACTI1)) / 3.0))
```

```
            FCNT(14,2) = EXGROW(I)
C       SORT TO FIND THE BEST METHOD
515     IFEDO = 0
        DO 520 ISORT = 1,13
            IF (FCNT(ISORT,1) .GT. FCNT(ISORT+1,1)) THEN
               SORTNR = FCNT(ISORT,1)
               SORTNR1 = FCNT(ISORT,2)
               FCNT(ISORT,1) = FCNT(ISORT+1,1)
               FCNT(ISORT,2) = FCNT(ISORT+1,2)
               FCNT(ISORT+1,1) = SORTNR
               FCNT(ISORT+1,2) = SORTNR1
               IFEDO = 1
            ENDIF
520     CONTINUE
            IF (IFEDO .EQ. 1) GO TO 515
        ICLECT(I) = FCNT(1,2)
510     CONTINUE
*******************************************************************
C       THIS ROUTINE CALCULATES THE MAD AND THE
C       TRACKING SIGNAL AND WRITES THEM OUT TO A FILE
C       SO THAT A ONEWAY ANAL OF VARIANCE CAN BE RUN.
*******************************************************************
C       CALCULATE THE MAD
        SUMNAIV = SUMMA4 = SUMMA8 = SUMMA12 = 0.0
        SUMDMA4 = SUMDMA8 = SUMDM12 = 0.0
        SUMSE2 = SUMSE8 = SUMSET = SUMFF = SUMSREG = SUMSC = SUMEX =
        SUMIC = 0.0
        DO 610 I = 13,38
            SUMNAIV = SUMNAIV + ABS(ACTUAL(I) - NAIVE(I))
            SUMMA4 = SUMMA4 + ABS(ACTUAL(I) - MA4(I))
            SUMMA8 = SUMMA8 + ABS(ACTUAL(I) - MA8(I))
            SUMMA12 = SUMMA12 + ABS(ACTUAL(I) - MA12(I))
            SUMDMA4 = SUMDMA4 + ABS(ACTUAL(I) - DMA4(I))
            SUMDMA8 = SUMDMA8 + ABS(ACTUAL(I) - DMA8(I))
            SUMDM12 = SUMDM12 + ABS(ACTUAL(I) - DMA12(I))
            SUMSE2 = SUMSE2 + ABS(ACTUAL(I) - SESNOT2(I))
            SUMSE8 = SUMSE8 + ABS(ACTUAL(I) - SESNOT8(I))
            SUMSET = SUMSET + ABS(ACTUAL(I) - SESTRND(I))
            SUMFF = SUMFF + ABS(ACTUAL(I)  - FF(I))
            SUMSREG = SUMSREG + ABS(ACTUAL(I) - SREG(I))
            SUMSC = SUMSC + ABS(ACTUAL(I) - SCURVE(I))
            SUMEX = SUMEX + ABS(ACTUAL(I) - EXGROW(I))
            SUMIC = SUMIC + ABS(ACTUAL(I) - ICLECT(I))
610     CONTINUE
        IMAD(1) = SUMNAIV / 26.0
        IMAD(2) = SUMMA4 / 26.0
        IMAD(3) = SUMMA8 / 26.0
        IMAD(4) = SUMMA12 / 26.0
        IMAD(5) = SUMDMA4 / 26.0
        IMAD(6) = SUMDMA8 / 26.0
```

```
      ZMAD(7) = SUMDM12 / 26.0
      ZMAD(8) = SUMSE2 / 26.0
      ZMAD(9) = SUMSE8 / 26.0
      ZMAD(10) = SUMSET / 26.0
      ZMAD(11) = SUMFF / 26.0
      ZMAD(12) = SUMSREG / 26.0
      ZMAD(13) = SUMSC / 26.0
      ZMAD(14) = SUMEX / 26.0
      ZMAD(15) = SUMIC / 26.0
C     CALCULATE THE TRACKING SIGNAL
      DO 615 I = 1,15
         SFE(I) = 0.0
         VAR(I) = 0.0
615   CONTINUE
      DO 620 I = 13,38
         SFE(1) = SFE(1) + (ACTUAL(I) - NAIVE(I))
         SFE(2) = SFE(2) + (ACTUAL(I) - MA4(I))
         SFE(3) = SFE(3) + (ACTUAL(I) - MA8(I))
         SFE(4) = SFE(4) + (ACTUAL(I) - MA12(I))
         SFE(5) = SFE(5) + (ACTUAL(I) - DMA4(I))
         SFE(6) = SFE(6) + (ACTUAL(I) - DMA8(I))
         SFE(7) = SFE(7) + (ACTUAL(I) - DMA12(I))
         SFE(8) = SFE(8) + (ACTUAL(I) - SESNOT2(I))
         SFE(9) = SFE(9) + (ACTUAL(I) - SESNOT8(I))
         SFE(10) = SFE(10) + (ACTUAL(I) - SESTRND(I))
         SFE(11) = SFE(11) + (ACTUAL(I) -  FF(I))
         SFE(12) = SFE(12) + (ACTUAL(I) - SREG(I))
         SFE(13) = SFE(13) + (ACTUAL(I) - SCURVE(I))
         SFE(14) = SFE(14) + (ACTUAL(I) - EXGROW(I))
         SFE(15) = SFE(15) + (ACTUAL(I) - ICLECT(I))
         VAR(1) = VAR(1) + (ACTUAL(I) - NAIVE(I))**2
         VAR(2) = VAR(2) + (ACTUAL(I) - MA4(I))**2
         VAR(3) = VAR(3) + (ACTUAL(I) - MA8(I))**2
         VAR(4) = VAR(4) + (ACTUAL(I) - MA12(I))**2
         VAR(5) = VAR(5) + (ACTUAL(I) - DMA4(I))**2
         VAR(6) = VAR(6) + (ACTUAL(I) - DMA8(I))**2
         VAR(7) = VAR(7) + (ACTUAL(I) - DMA12(I))**2
         VAR(8) = VAR(8) + (ACTUAL(I) - SESNOT2(I))**2
         VAR(9) = VAR(9) + (ACTUAL(I) -SESNOT8(I))**2
         VAR(10) = VAR(10) + (ACTUAL(I) - SESTRND(I))**2
         VAR(11) = VAR(11) + (ACTUAL(I) - FF(I))**2
         VAR(12) = VAR(12) + (ACTUAL(I) - SREG(I))**2
         VAR(13) = VAR(13) + (ACTUAL(I) - SCURVE(I))**2
         VAR(14) = VAR(14) + (ACTUAL(I) - EXGROW(I))**2
         VAR(15) = VAR(15) + (ACTUAL(I) - ICLECT(I))**2
620   CONTINUE
      DO 625 K = 1,15
         TRSIG(K) = SFE(K) / ZMAD(K)
         VAR(K) = VAR(K) / 26.0
         AVMAD(K) = AVMAD(K) + ZMAD(K)
```

```
            AVTRS(K) = AVTRS(K) + TRSIG(K)
            AVVAR(K) = AVVAR(K) + VAR(K)
575     CONTINUE
        MADCNTR = MADCNTR + 1
        GO TO 20
************************************************************************
C       THE FOLLOWING CODE HANDLES END OF FILE CONDITION
************************************************************************
999     DO 700 I = 1,15
            AVMAD(I) = AVMAD(I) / MADCNTR
            AVTRS(I) = AVTRS(I) / MADCNTR
            AVVAR(I) = AVVAR(I) / MADCNTR
700     CONTINUE
        X1 = AVMAD(15) * 100.0
        DO 710 I = 1,15
            AVE(I) = X1 / AVMAD(I)
710     CONTINUE
        WRITE(IW,570) (AVMAD(I),I=1,15)
        WRITE(IW,570) (AVTRS(I),I=1,15)
        WRITE(IW,570) (AVVAR(I),I=1,15)
570     FORMAT(15(F7.2,1X))
        END
************************************************************************
************************************************************************
C       THE FOLLOWING CODE IS PLACED IN THE DESIGNATED AREAS TO ACHIEVE 3
C       DIFFERENT RUNS OF CALCULATIONS OF CERTAIN VARIABLES
************************************************************************
C       THE FOLLOWING CODE REPLACE THE ECLECTIC FORECASTING CODE
C       AND CALCULATES THE ECLECTIC FORECAST BY CHOOSING THE
C       BEST METHOD FROM THE FORECASTING TECHNIQUE WHICH
C       WAS CLOSEST TO THE ACTUAL IN THE LAST PERIOD.
************************************************************************
        DO 500 I = 1,8
            ICLECT(I) = ACTUAL(I)
500     CONTINUE
        DO 510 I = 9,78
            BEST(1) = ABS(ACTUAL(I) - NAIVE(I))
            BEST(2) = ABS(ACTUAL(I) - MA4(I))
            BEST(3) = ABS(ACTUAL(I) - MA8(I))
            BEST(4) = ABS(ACTUAL(I) - MA12(I))
            BEST(5) = ABS(ACTUAL(I) - DMA4(I))
            BEST(6) = ABS(ACTUAL(I) - DMA8(I))
            BEST(7) = ABS(ACTUAL(I) - DMA12(I))
            BEST(8) = ABS(ACTUAL(I) - SESNOT2(I))
            BEST(9) = ABS(ACTUAL(I) - SESNOT8(I))
            BEST(10) = ABS(ACTUAL(I) - SESTRND(I))
            BEST(11) = ABS(ACTUAL(I) - FF(I))
            BEST(12) = ABS(ACTUAL(I) - SREG(I))
            BEST(13) = ABS(ACTUAL(I) - SCURVE(I))
            BEST(14) = ABS(ACTUAL(I) - EXGROW(I))
```

```
C      SORT TO FIND THE LOWEST VALUE
515    IREDO = 0
       DO 520 ISORT = 1,IT
          IF (BEST(ISORT) .GT. BEST(ISORT+1)) THEN
             SORTNR = BEST(ISORT)
             BEST(ISORT) = BEST(ISORT+1)
             BEST(ISORT+1) = SORTNR
             IREDO = 1
          ENDIF
520    CONTINUE
       IF (IREDO .EQ. 1) GO TO 515
       ICLECT(I) = BEST(1)
510    CONTINUE
*******************************************************************
C      THE FOLLOWING CODE HANDLES THE WEIGHTING TECHNIQUE
C      FOR THE ECLECTIC METHOD. IT CAN REPLACE THE LINE --
C      ICLECT(I) = ...........
C      AT THE END OF ANY ECLECTIC FORECASTING CALCULATION.
*******************************************************************
C      NOTE. PCNT(1,1) ETC MUST BE CHANGED TO BEST(1) ETC
C      DEPENDING ON WHICH RUN YOU ARE USING.
*******************************************************************
       ADDIT = PCNT(1,1) + PCNT(2,1) + PCNT(3,1)
       IF (ADDIT .EQ. 0) THEN
          ICLECT(I) = PCNT(1,2)
          GO TO 510
       ENDIF
       ACNT = PCNT(1,1) / ADDIT
       BCNT = PCNT(2,1) / ADDIT
       CCNT = PCNT(3,1) / ADDIT
       AONE = 1.0 - ACNT
       BONE = 1.0 - BCNT
       CONE = 1.0 - CCNT
       ADDIT = AONE + BONE + CONE
       ACNT = AONE / ADDIT
       BCNT = BONE / ADDIT
       CCNT = CONE / ADDIT
       ICLECT(I) = (ACNT * PCNT(1,2) + BCNT * PCNT(2,2) +
      +CCNT * PCNT(3,2))
*******************************************************************
*******************************************************************
```

A. REFERENCES CITED

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